



Wind of change : on the use of patents in the wind power industry

Valentin Lignau

► To cite this version:

Valentin Lignau. Wind of change : on the use of patents in the wind power industry. Economies et finances. Université de Nanterre - Paris X, 2023. Français. <NNT : 2023PA100015>. <tel-04203410>

HAL Id: tel-04203410

<https://theses.hal.science/tel-04203410v1>

Submitted on 11 Sep 2023

HAL is a multi-disciplinary open access archive for the deposit and dissemination of scientific research documents, whether they are published or not. The documents may come from teaching and research institutions in France or abroad, or from public or private research centers.

L'archive ouverte pluridisciplinaire **HAL**, est destinée au dépôt et à la diffusion de documents scientifiques de niveau recherche, publiés ou non, émanant des établissements d'enseignement et de recherche français ou étrangers, des laboratoires publics ou privés.



HAL Authorization

Membre de l'université Paris Lumières

Valentin Lignau

Wind of change

On the use of patents in the wind power industry

Thèse présentée et soutenue publiquement le 08/02/2023

en vue de l'obtention du doctorat de Sciences économiques de l'Université Paris Nanterre
sous la co-direction de Prof. Dr. Marc Baudry (Université Paris Nanterre)
et de Prof. Dr. Béatrice Dumont (Université Sorbonne Paris Nord, College of Europe)

Jury :

Rapporteur :	Prof. Dr. René Aïd	Professeur des Universités, Université Paris Dauphine
Rapporteur :	Prof. Dr. Dietmar Harhoff	Geschäftsführender Direktor am Max-Planck-Institut für Innovation und Wettbewerb, Honorarprofessor an der Ludwig-Maximilians-Universität München
Membre du jury :	Dr. Dominique Guellec	Conseiller scientifique, Observatoire des Sciences et Techniques
Membre du jury :	Dr. Román Arjona	Chief Economist, DG for Internal Market, Industry, Entrepreneurship and SMEs (GROW)
Membre du jury :	Prof. Dr. Eric Langlais	Professeur des Universités, Université Paris Nanterre

Remerciements

La rédaction des remerciements d'une thèse est, je crois, l'objet d'une grande attente pour son auteur. Elle marque la fin de plusieurs années de travail et est pour moi l'occasion d'exprimer toute ma gratitude à ceux qui ont contribué, de près ou de loin, à son bon déroulé.

Mes premiers remerciements s'adressent tout naturellement à mes directeurs de thèse. Je remercie Marc Baudry et Béatrice Dumont, dont l'accompagnement tout au long de ces quatre années a été précieux. Leur disponibilité et leur bienveillance, associées à leur maîtrise sans faille de la théorie économique et des sujets d'innovation, m'ont beaucoup apporté, tant dans le cadre de mes travaux que d'un point de vue plus personnel. Je vous remercie pour votre confiance et espère que ce travail sera à la hauteur de vos attentes. Je remercie également René Aïd, Dietmar Harhoff, Román Arjona, Dominique Guellec et Eric Langlais d'avoir accepté de constituer le jury de cette thèse. C'est un honneur de vous soumettre ce travail, et j'espère que vous le trouverez digne d'intérêt.

Le cadre dans lequel évolue un doctorant revêt une importance particulière. J'ai eu la chance de travailler au sein de la Chaire Economie du Climat qui, au-delà d'apporter un soutien matériel et un cadre intellectuel stimulant, a représenté pour moi un lieu d'épanouissement. Je remercie ses directeur et directrice successifs, Christian de Perthuis et Anna Creti, qui ont fait et font toujours de cette belle structure ce qu'elle est. Un grand merci également à Claire qui, en plus d'avoir si souvent su répondre à mes nombreuses interrogations, n'a jamais été avare en bons plans s'agissant du 5^{ème} arrondissement. J'ai également une pensée amicale pour Raphaël Trotignon, dont la présence à la Chaire alors que j'y faisais mes premiers pas a été très importante à mes yeux. Cette aventure n'aurait pu voir le jour sans l'aval du laboratoire EconomiX, dont j'ai beaucoup apprécié l'atmosphère bienveillante. Merci à ses directrices successives, Valérie Mignon et Nadine Levratto, de faire vivre ce laboratoire. Un grand merci également à Frédéric Hammerer, dont la disponibilité n'a jamais fait défaut, ainsi qu'à Isabelle Tripet, d'avoir toujours su m'aiguiller dans mes démarches administratives.

Les quatre années passées, et c'est peut-être là le plus important, ont été l'occasion de rencontres qui ont pour certaines évolué en de solides amitiés. Je remercie chaleureusement

Côme, pour toutes nos discussions, sérieuses et moins sérieuses ; Raphaël, dont la curiosité n'a de cesse de m'inspirer ; Olivier, qui a été et continue d'être un moteur de ma vie sociale. A vous trois, j'espère que l'on continuera longtemps encore à arpenter les salons en tout genre. Merci aussi à Maxime et Quentin de m'avoir fait découvrir les meilleures adresses du quartier de la BNF. Mes pensées vont également à mes collègues, présents et passés, de la Chaire Economie du Climat, à qui je souhaite tout le meilleur : Adrien, Aliénor, Anouk, Camille, Coline, Edouard C., Edouard P., Esther, Etienne, Giulia, Jérôme, Léa, Mamadou, Marie, Milien, Mohamed, Nathaly, Richard, Théotime, Tom et Valentin. Merci également à l'ensemble des doctorants de Nanterre qui contribuent pour beaucoup à l'ambiance chaleureuse qui y règne. Je pense notamment à Baptiste, Capucine, Chouaib, Claire, Emmanuelle, Fanny, Harouna, Lesly, Liza, Mathilde, Maxime, Olivier et Remy. Je remercie tout particulièrement Kymble pour son aide, même bien après la fin de sa thèse.

Fort heureusement, l'écriture du présent manuscrit a laissé suffisamment d'espace aux interactions extra-professionnelles pour qu'une partie de ces remerciements soit dédiée à mes amis de longue date. Je tiens en premier lieu à remercier les membres des Craps, avec lesquels je me réjouis de contribuer à la liesse propre aux fêtes de Bayonne. J'ai une pensée toute particulière pour Thomas et Xavier pour leur présence en toutes circonstances, ainsi que pour Clément, Olivier et Robin. Certaines personnes qui m'ont accompagné à différents moments de mon cursus méritent aussi d'être remerciées. J'ai évidemment une pensée pour Julien et Maxime, co-auteurs du TER de seconde année qui a éveillé en moi un attrait conjoint pour la recherche académique et la géographie française, ainsi que pour Mathias D. et Mathias E. pour tous les bons moments passés ensemble. Merci à Lounes et Quentin, avec qui les récurrents rendez-vous aux Halles sont toujours des plus rafraîchissants. Merci aussi au reste de l'équipe de Nantes - Antoine, Arthur, Yvain – que j'ai toujours plaisir à revoir malgré l'éloignement géographique. Un grand merci à Adrien, d'avoir emmené un peu de Sud-Ouest à Paris pendant ces années et pour ses mots toujours motivants. Merci également à Alissa et Guillaume ainsi qu'à Henry et Lola de rythmer ma vie parisienne. Enfin, quelques remerciements plus épars à Manon et Damien, Mathilde S. et Mathieu avec qui les moments passés, quoique trop peu nombreux, sont chers à mes yeux.

Ces dernières lignes, pourtant non des moindres, s'adressent à ma famille. Un grand merci à mes parents pour l'infinité de choses qu'ils font pour moi, ainsi qu'à ma sœur Margaux, à qui je souhaite beaucoup de bonnes choses dans sa nouvelle vie parisienne. Merci enfin à Mathilde, pour son indéfectible soutien jusque dans les dernières minutes de ce travail. Te côtoyer chaque jour est une véritable source de motivation.

Wind of change: On the use of patents in the wind power industry

Abstract

Studying the relationship between patents and innovation is worthwhile in at least two respects. First, it provides information about the efficiency of the patent system in fulfilling its original objective of promoting innovation. Second, it is informative about the relevance of relying on patent counts to proxy the inventive activity of firms or countries. The purpose of this thesis is to analyze this relationship in the context of a “green” technology, namely wind power. Low-carbon innovation policies usually imply generic policy instruments – such as a patent system – that are supposed to encourage firms to invest in the R&D process while directing technical change by relying on environmental policy instruments. In this regard, the patent system has a key role to play in achieving climate goals, both as a measure and a driver of a low-carbon innovation policy. The first chapter deals with the issue of “strategic” uses of patents through the prism of patent oppositions. By examining the determinants of both oppositions and their outcomes, it aims at assessing whether “misuses” of patents and oppositions are common practices in the field. The second chapter aims at distinguishing patents covering product and process inventions based on a semantic analysis of patents’ descriptions. This work plays a pivotal role as it serves the two following chapters. The latter are both attempts to assess whether firms holding patents are those having actual contributions to technical change, but they differ in the way they capture these contributions. The third chapter focuses on product innovation and studies the relationship between patents and improvements in technical characteristics of turbines. The fourth chapter follows the very same logic but is interested in process innovation and the decrease in the cost of technology. Ultimately, based on an extensive study of the wind power industry, there is no evidence that the European patent system fails in its objective of catalyzing innovation.

Keywords – Patents, low-carbon innovation, environmental policy, onshore wind power, empirical economics

Wind of change : De l’usage des brevets dans l’industrie de l’énergie éolienne

Résumé

L’étude de la relation entre brevets et innovation présente un intérêt à au moins deux égards. D’une part, elle permet d’apprécier si le système des brevets est un instrument efficace dans son rôle originel de catalyseur de l’innovation. D’autre part, elle apporte une information sur la pertinence du recours aux données de brevets comme reflet de l’activité inventive des firmes ou des pays. L’objectif de cette thèse est d’étudier cette relation dans le cadre de la technologie bas-carbone qu’est l’énergie éolienne. La solution retenue par les pouvoirs publics en matière d’innovation « verte » est bien souvent le couplage entre une politique visant à inciter les agents économiques à s’engager dans le processus de R&D – un système de brevets s’inscrivant dans cette logique – et une politique visant à orienter cet effort de recherche vers des technologies propres. En ce sens, le système des brevets a un rôle clé à jouer dans la réalisation des objectifs climatiques, tant comme instrument de suivi que de conduite de la politique d’innovation bas-carbone. Le premier chapitre aborde la question des usages dits « stratégiques » des brevets sous le prisme de la procédure d’opposition. Plus précisément, il s’agit d’étudier, en examinant les déterminants des oppositions de brevets et de l’issue de ces oppositions, si les comportements des firmes mettent en lumière de tels usages. Dans un deuxième chapitre, nous cherchons à distinguer par des techniques d’analyse sémantique les brevets relevant de l’innovation de produit des brevets couvrant des inventions de procédé. Ce chapitre joue un rôle charnière en alimentant les chapitres subséquents. Tous deux cherchent à apprécier si les firmes qui détiennent les brevets sont celles qui contribuent de manière effective au progrès technique, mais diffèrent quant à la mesure de ces contributions. Le troisième chapitre s’intéresse à l’innovation de produit, et plus spécifiquement à la relation entre brevets et évolution dans les caractéristiques techniques des turbines. Le quatrième chapitre suit la même logique, mais se concentre sur l’innovation de procédé et la baisse du coût de la technologie. Finalement, sur la base d’une étude de l’industrie de l’énergie éolienne, rien n’indique que le système européen des brevets échoue à remplir sa fonction d’incitation à l’innovation.

Mots Clés – Brevets, innovation bas-carbone, politique environnementale, éolien terrestre, économie empirique

Table of Contents

Remerciements	i
Abstract	iii
Résumé	iv
General Introduction	1
1 Use or Abuse of Patent Oppositions? Evidence from the Wind Power Industry	21
1.1 Introduction	22
1.2 Oppositions and their determinants: an overview	25
1.2.1 The opposition procedure at the EPO	25
1.2.2 Elements of literature	28
1.2.3 Contributions	32
1.3 New insights on the determinants of oppositions and their outcomes	36
1.3.1 Data	36
1.3.2 Method	47
1.3.3 Estimation and results	50
1.4 Conclusion	58
Appendices of Chapter 1	59
1.A Robustness	60
1.A.1 First step	60
1.A.2 Second step	61
2 On the identification of process and product innovations: New insights from text mining techniques	65
2.1 Introduction	66
2.2 The non-neutrality of renewables support policies on the type of innovation induced	67

2.2.1	How does the wholesale electricity market works?	68
2.2.2	Public policies and the return on investments on wind power generation	69
2.2.3	What type of innovation is fostered by what type of policy?	71
2.3	Methodology to disentangle patents on process innovation and patents on product innovation	72
2.3.1	Semantic treatment of patents' text	72
2.3.2	The polar coordinates approach	75
2.4	Application to wind power patents granted by the EPO	76
2.4.1	Data	77
2.4.2	Results	77
2.4.3	Exploring the link with public policies	82
2.5	Conclusion	85
3	Do patent holders push the technology frontier forward? Evidence from the wind power industry	89
3.1	Introduction	90
3.2	The measurement of firm-level contributions to technical change	94
3.2.1	Some basic wind energy physics	94
3.2.2	Technology frontier and contributions to technical change	98
3.2.3	Data and facts	102
3.3	Firms' patent portfolio size <i>vs</i> contribution to technical change	107
3.3.1	Patent counts and the <i>knowledge stock</i>	107
3.3.2	On the patent – technical change relationship	111
3.4	Conclusion	118
	Appendices of Chapter 3	121
3.A	Computing the Annual Energy Production (<i>AEP</i>)	121
3.B	Main manufacturers considered in our sample	123
4	Patents, process innovation and the cost of wind turbines: A first look	127
4.1	Introduction	128
4.2	The choice of a wind turbine: theoretical elements	130
4.3	Data collection and processing	132
4.4	Modeling individual choices: the conditional <i>logit</i>	137
4.5	Results and discussion	139
4.6	Conclusion	146
	Appendices of Chapter 4	149

4.A	Graphs in absolute values	149
4.A.1	Market share	149
4.A.2	Average processness	150
4.A.3	Characteristics of commissioned turbines	151
	Concluding remarks	155
	Bibliography	161
	Résumé long	173

List of Figures

1	Evolution in the number of wind power-related patented inventions, 1890-2020 <i>Source: PATSTAT database</i>	4
1.1	Number of installed turbines and opposed patents in the European wind power sector (cumulation), 1990-2017	37
1.2	Number of oppositions per patent, 1990-2019	37
1.3	Count of opposed patents according to the outcome of the opposition procedure, 1990-2019	38
1.4	Outcomes of oppositions, by applicant (1990-2019)	40
1.5	Outcomes of initiated oppositions, by opponent (1990-2019)	40
1.6	Count of opposed patents according to their resilience to opposition	42
2.2.1	Wholesale electricity market under a feed-in tariff regime	69
2.2.2	Wholesale electricity market under a CO ₂ pricing regime	71
2.3.1	“Product character” of a given patent i	75
2.4.1	Distribution of φ in our sample ($N = 5,399$)	78
2.4.2	Relationship between φ and the amount of information involved (r)	79
2.4.3	Relationship between φ and the share of field-specific product keywords	79
2.4.4	Evolution in the share of French or German written patents	81
2.4.5	Chronological evolution in the distribution of φ	81
2.4.6	Evolution in the number of product ($\varphi > 0.5$) and process ($\varphi < 0.5$) patents	82
2.4.7	Evolution in the number of pure product ($\varphi = 1$) and pure process ($\varphi = 0$) patents	82
2.4.8	Cumulative wind power installed capacities within the EPO area and worldwide <i>Data source: Global Wind Energy Council and European Wind Energy Association</i>	83
2.4.9	Comparison of FIT support and CO ₂ pricing support <i>Data source: OECD and EEX</i>	85
3.2.1	Power curve, power coefficient and the Betz’s law	95

3.2.2	AEP computation for the Vestas V90/2000 IEC II wind turbine model . . .	97
3.2.3	Contribution based on radial distances	99
3.2.4	Contribution based on isoquants	100
3.2.5	Contribution to absolute <i>AEP</i>	101
3.2.6	Contribution to absolute <i>AEP</i> (FDH method)	102
3.2.7	2017 frontier, by IEC wind class	103
3.2.8	New models entering the market, by IEC class, 2000-2017	104
3.2.9	Evolution of the IEC II wind turbines frontier, 2000-2016	105
3.2.10	Distribution of θ_1 measure	106
3.2.11	Distribution of θ_2 measure	106
3.2.12	Summary of firms' contributions over the 2000–2017 period	107
3.3.1	Distribution of φ in our sample ($N = 5,367$)	109
3.3.2	Distribution of the forward citation index in our sample ($N = 5,367$) . . .	111
3.3.3	Knowledge stock estimations	112
3.3.4	Correlation between the number of innovative models and the number of granted patents over the 2000-2017 period	112
3.3.5	Patent portfolios and contributions to technical change	117
3.3.6	Evolution in the installed capacity and in the number of patents, 1990-2017	118
3.3.7	Evolution in the HHI and maximum contributions on the European on- shore wind turbines market, 1990-2017	118
3.A.1	AEP computation for the Vestas V90/2000 IEC II wind turbine model . .	122
4.3.1	Parks included in the sample	135
4.3.2	Differences between manufacturers according to several turbine character- istics, relative to the annual average characteristic computed for commis- sioned turbines	137
4.5.1	Marginal effects for the year dummies (relative to year 2008)	142
4.5.2	Evolution in the observed market shares (relative to year 2008)	143
4.5.3	Evolution in the relative average “processness” of patents and patent port- folios	144
4.5.4	Evolution in relative global patent filing and portfolio size	145
4.5.5	Evolution in relative experience	146
4.A.1	Evolution in the market shares of firms	149
4.A.2	Evolution in the “processness” of patents and patent portfolios, by firm . .	150
4.A.3	Evolution in the characteristics of installed turbines	151

List of Tables

1.1	Summary of the literature relative to patent oppositions	28
1.2	Conjectures relative to patent oppositions	31
1.3	Matrix of oppositions between players of the wind power industry, 2000-2019	39
1.4	Descriptive statistics for the first-step final sample	46
1.5	Descriptive statistics for the second-step final sample	47
1.6	Probit (1), negative binomial (2), zero-inflated Poisson (3) and zero-inflated negative binomial (4) specifications for opposition likelihood (1) and op- ponents count (2, 3, 4)	52
1.7	Confirmation of previous conjectures	53
1.8	Estimates for stepwise probit, ordered logit and beta regressions	54
1.9	Zero-one inflated beta regressions for resilience to opposition	57
1.A.1	Probit and negative binomial specifications for resp. opposition likelihood and opponents count. Data: population of patents granted to wind turbine manufacturers.	60
1.A.2	Estimates for stepwise probit, ordered logit and beta regressions. Data: sample of patents granted to wind turbine manufacturers that have been opposed and for which the EPO have settled the case.	61
2.3.1	Selected keywords	74
2.4.1	Summary statistics for φ , by language	80
2.4.2	Kolmogorov-Smirnov two-sided test	82
3.2.1	IEC wind classes and associated average wind speeds	96
3.2.2	Summary statistics	106
3.3.1	Selected CPC classes and associated descriptions	108
3.3.2	Introduction of the variables	114
3.3.3	Best-fitting fixed effects regressions	115
3.3.4	Estimated fixed effects for model (2)	116
3.A.1	IEC wind classes and associated average wind speeds	122
3.B.1	Main wind turbine manufacturers	123

4.3.1	Example of a choice situation: Langres Sud wind farm (Haute-Marne, France)	136
4.4.1	Variables description	140
4.5.1	Estimation	140
4.5.2	Actual and predicted market shares	141

List of Acronyms

AEP	Annual Energy Production
AME	Average Marginal Effect
CPC	Cooperative Patent Classification
DEA	Data Envelopment Analysis
EEA	European Economic Area
EPC	European Patent Convention
EPO	European Patent Office
FDH	Free Disposal Hull
FIT	Feed-in Tariff
GHG	Greenhouse Gas
HHI	Herfindahl-Hirschmann Index
IEC	International Electrotechnical Commission
IPC	International Patent Classification
IPR	Intellectual Property Right
NPV	Net Present Value
OEM	Original Equipment Manufacturer
O&M	Operation and Maintenance
R&D	Research and Development
USPTO	United States Patents and Trademarks Office
WT	Wind Turbine
ZINB	Zero Inflated Negative Binomial
ZIP	Zero Inflated Poisson
ZOIB	Zero-One Inflated Beta

* * *

General Introduction

INNOVATION is traditionally seen as the fuel for economic growth. By increasing factor productivity, it is credited to have helped improving living standards for millennia, and especially since the first industrial revolution. However, the 1972 *Limits to Growth* report commissioned by the Club of Rome has considerably contributed to open the world's eyes to environmental issues associated with the pursuit of economic growth in a context of constrained resources. Fifty years later, while the idea of tackling environmental issues through more sober ways of life is gaining ground, innovation remains an important lever in the objective of maintaining – and bettering – living conditions while reducing the associated resources consumption and greenhouse gases (GHG) emissions. One important challenge is to direct research investments toward *clean* or *green*, i.e. environment-friendly technologies. From an economic point of view, fulfilling this objective requires tackling both technological and environmental externalities. On the one hand, the non-rival character of knowledge and the high costs and uncertainty associated with its creation induce lower research investments than what would be socially desirable.¹ On the other hand, environmental damages caused by polluting activities are poorly accounted for in agents' decisions as they will be borne by future generations.

Paradoxically, while being considered as (part of) the solution to climate change, innovation has initially been one important driver of it. Indeed, the important improvements in the living standards experienced since the industrial revolution came along with an important increase in greenhouse gases emissions. One noticeable example is coal extraction, that has benefited from a major invention from the late 18th century, namely steam engine. After having lowered the cost of coal by allowing for deeper delving in mines, steam engine has then experienced a multiplication of uses, especially in transportation. Nowadays, coal is still quite widely used for electricity generation and is responsible for a major part of GHG emissions in the power generator sector at a worldwide level. Data from the National Oceanic and Atmospheric Administration (NOAA) evidence that CO₂ concentration in the

¹Other well documented issues are informational and learning externalities that play a crucial role in later stages of adoption and diffusion of technologies. They will not be at the core of this thesis' discussions.

atmosphere has evolved from 279.6 ppm in year 1000 to 288.2 ppm in 1870, then to 421 ppm in 2022. Consequently, world average temperature has increase by almost 1 celsius degree relative to pre-industrial times. Since its creation in 1988, the Intergovernmental Panel on Climate Change (IPCC) has warned about further alarming consequences of climate change, both direct (e.g. rising oceans level, increased frequency of extreme events, biodiversity losses) and indirect (e.g. health troubles).

Currently, the energy sector is still a major emitter. According to data from the European Environment Agency (EEA), energy production was responsible for around 25.8% of the 2019 European GHG emissions. The main objectives of the European energy policy are (i) to ensure energy security, (ii) to provide affordable energy for final consumers and (iii) to tackle climate change.² In this context, renewable energy appears to provide several eggs in a same basket: the required primary sources of energy are (i) provided by nature – thus available everywhere – (ii) at no (marginal) cost, (iii) in addition to be carbon-neutral. As a consequence, one aim of the 2015 Energy Union program is to “*promote research in low-carbon and clean energy technologies, and prioritise research and innovation to drive the energy transition and improve competitiveness*”. The promotion of low-carbon technologies is for instance one pillar of the 2019 European Green Deal program, which ambition is to reduce GHG emissions by 55% in 2030 (relative to 1990 level) and to reach carbon neutrality by year 2050. For this purpose, the Innovation Fund created in 2015 is supposed to foster the development and commercialisation of innovative green technologies, including “*innovative renewable energy generation*” technologies. It is mainly financed by the revenue from auctioning a predefined quantity of EU Emissions Trading System (EU-ETS) allowances (around 450 millions between 2020 and 2030 representing EUR 38 billion at EUR 75/tCO₂). The more generic Horizon Europe programme (the European Union Research and Innovation programme), deployed over the 2021-2027 period, plans to dedicate 35% of its EUR 95.5 billion budget to address the climate change issue.³ For instance, the EUR 10 million “Sustainable, secure and competitive energy supply” call for funding (HORIZON-CL5-2021-D3-03) included 3 wind-power-related challenges.

Among renewable energy sources, wind has – along with hydropower – probably been the most widely exploited. From thousands-of-years-old sailboats to current hundred-meters-high wind turbines through wind mills and wind pumps, humans have for a long time taken advantage of the kinetic energy of wind. The first electricity generating turbine developed by the American inventor Charles F. Brush (1888) was equipped with a 12kW dynamo. The

²Other objectives include European market integration and improvements in energy efficiency.

³The Horizon programme should not be confused with Horizon prizes, that are *inducement prizes* that the European Commission mobilizes to make firms compete to overcome pre-defined challenges.

latest **Haliade-X** turbine from General Electric (GE), that should be soon commissioned at Dogger Bank Wind Farm (United-Kingdom), has a rated power of 14,000kW. About the turbine, the park's website advertises that “*one rotation [...] can power a UK household for two days*”. It makes no doubt that considerable research efforts have been undertaken to achieve such a result. The European Patent Office (EPO) records 173,121 patent applications filed across the world between 1890 and 2020 for wind power (CPC Class Y02E 10/7). They cover 102,954 unique inventions among which about 95% have been discovered from 1980 onwards. From the THEWINDPOWER database, and focusing on “actual” technological evolution, turbines commercialized before 1980 had a maximal rated power of 600kW. One can expect the increasing trend in turbines' rated power to follow on as by 2028, according to a recent study by IntelStor, the worldwide wind power industry is expected to spend USD 28.2 billion in private research and development (R&D) that should be complemented with USD 8.7 billion in public expenditures.⁴ According to Wood Mackenzie, R&D spending from the top ten wind turbine original equipment manufacturers (OEMs) reached EUR 1.6 billion in 2018 and should amount to EUR 2.3 billion by 2023.⁵

The evolution in the number of worldwide patented inventions, highlighted by Figure 1, follows a time path similar to that of the development and diffusion of technology.⁶ The renewed interest for wind power in the 1970s can be explained by public support from pioneering countries such as Denmark or Germany to the wind power technology⁷ through both *supply-push* and *market-pull* instruments.⁸ Supply-push or *technology-push* instruments aim at fostering “radical” discoveries independently from expressed consumer needs. Research tax credit or research subsidies are examples of such instruments. The latter have for instance been implemented from 1976 onwards in Denmark. The objective of market-pull or *demand-pull* instruments is to stimulate demand for a given technology, thus increasing profit opportunities and incentivizing research investments. Systems that spearheaded *feed-in tariffs* are part of these and have for instance been implemented since 1979 in Germany.⁹ Technology maturity is an important factor in tipping the balance toward one specific category of instruments: while supply-push strategies are relevant in the earliest (longer

⁴<https://www.windpowerengineering.com/wind-rd-spending-to-top-36-9-billion-by-2028/>, consulted on October 12th, 2019.

⁵<https://www.woodmac.com/press-releases/top-ten-wind-turbine-oems-to-spend-2.3bn-on-rd-by-2023/>, consulted on October 12th, 2019.

⁶The number of inventions has been retrieved thanks to the family identifier of patents: a *patent family* regroups all patents that relate to the same invention.

⁷These policies did target renewable energy sources in general, but factors such as local climate and geographical conditions have quite naturally directed innovation towards wind power.

⁸For more details about these instruments and their evolution, see e.g. Godin and Lane (2013).

⁹It is interesting to notice that wind turbine manufacturers from these countries (e.g. Danish company Vestas and German companies Enercon and Nordex) are still leading companies on the market.

and more uncertain) stages of the innovation process, demand-pull instruments require the pre-existence of knowledge and tend to foster incremental innovation.

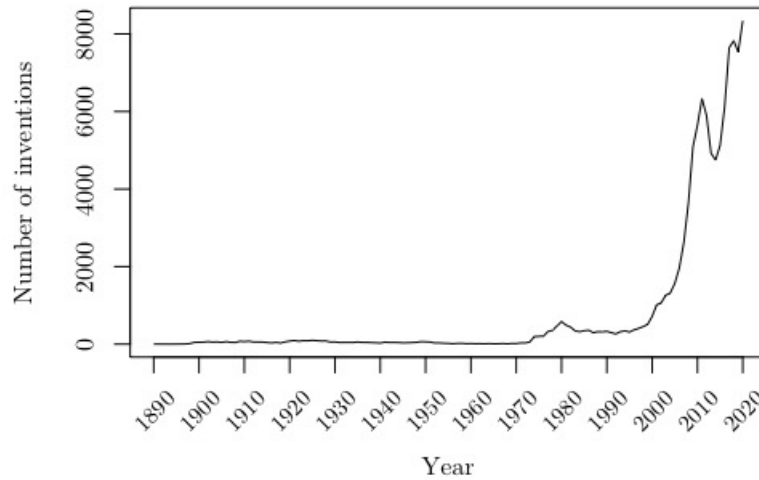


Figure 1: Evolution in the number of wind power-related patented inventions, 1890-2020

Source: PATSTAT database

The figures displayed above raise two important issues that will be extensively studied in this thesis. The first one relates to patents and technical change. As will be detailed below, the patent system, by rewarding successful inventors with a right to exclude any third person from the use of the underlying invention, is supposed to provide an incentive to economic agents to get involved in research activities. The fact that, between 1890 and 1980, 5% of patented inventions have contributed to multiply by 50 the rated power of turbines (from 12kW to 600kW) while the remaining 95%, patented between 1980 and 2020, have led to an increase by a factor of around 23 (from 600kW to 14,000kW) could make one wonder about the relevance of such a system. If this particular phenomenon can be explained by decreasing marginal returns or changes in the economic context, the economic literature has for a long time expressed doubts about the ability of the patent system to fulfill its original objective of properly inducing technological change. The second issue is about patent counts as the outcome of innovation – and especially green innovation – policies. Does an increase in patenting activity in response to policy implementation reflect the efficiency of this policy? Once again, results from previous contributions makes the answer ambiguous. Especially, it has been emphasised that (i) not all inventions are subject to patent protection, and (ii) there is an heterogeneity in the social value generated by patented inventions. The exercise we conducted when commenting Figure 1 in the light of environmental policy is thus quite

a tricky one. The following sections dig deeper into these questions and present the related academic state of art.

Patents as a response to the knowledge externality

It is usually considered that the promulgation in 1474 of the *Parte Veneziana* has paved the way to our current patent systems. While practise has anticipated the economic formulation of innovation issues, a patent system can fairly be justified from an economist's point of view. Economic theory has shown – on the basis of Nelson (1959) and Arrow (1962) – that a *laissez faire* situation induces an under-investment in R&D activities and has emphasized the need to encourage firms to engage in the creation of knowledge. This phenomenon results from the so-called *problem of appropriability* which source is twofold. On the one hand, this process is uncertain in addition to be costly.¹⁰ A rational agent will only mobilize the required resources if the expected value of the resulting innovation¹¹ exceeds the cost of these resources. On the other hand, knowledge has the characteristics of a public good. Indeed, it is intrinsically non-rival (i.e. the use of knowledge by an agent does not impede its use by another one) as well as non-excludable (i.e. it is impossible – or at least very costly – to restrict access to knowledge). The former property implies that knowledge can be reproduced at no cost (or maybe the one of understanding). The second property makes possible the implementation by potential competitors which, unlike the original inventor, have not supported the inherent research costs. This can lead to a situation in which the market price of the innovation is such that the inventor is not capable of recovering its investment while imitators earn positive profits. In such a context, everyone's interest lies in waiting for the invention to be discovered by someone else and no one is willing to get involved in the research process. The regulator thus faces a typical *free-rider* problem.

However, the ability to exclude third parties from the use of a novel idea depends on the possibility of *reverse engineering*. In a technological monitoring context, it consists in dismantling the final version of an innovation to retrieve the innovative principle of it. The more effort is required to (re)discover the invention's content, the easier is the exclusion. In cases where reverse engineering is intricate, trade secret may be sufficient for the inventor to prevent imitation of the underlying idea. Otherwise, a patent system makes sense in that it allows to make knowledge excludable. A patent can be defined as a right to exclude any third party from any use of the patented invention. As long as the patent is “alive”,

¹⁰Moreover, research costs can be considered to be sunk costs. The required investment in the creation of knowledge can not be recovered in another way than the one of monetizing the output of the research process (by commercializing the subsequent innovation or by leasing or selling a potential property right on the idea).

¹¹In the *schumpeterian* perspective, it is considered that an innovation is the commercial achievement of an invention.

its holder has the possibility to restrict access to the invention – enjoying market power due to a monopoly position or a differentiation strategy –, or to request royalties for this access. It is worthwhile to notice that he also has the possibility to provide a free access for it, making patents complementary with open innovation systems. With such a system, the incentive to innovate goes along with a socially harmful dead weight loss. Hereafter, this loss will be referred to as the *social cost* of the patent system. The patent is thus a *second best* instrument and the question about the optimal design (trade-off between *static inefficiency* and *dynamic efficiency*) has been raised quite early by the seminal work of Nordhaus (1967, 1969b) which has given birth to an abundant literature. The search of optimal patent *length* (i.e. lifetime), *breadth* (i.e. patent technological scope) and *height* (i.e. degree of novelty in cases of incremental innovations) has contributed to shape our current patent system: a limited lifetime (up to 20 years in most countries), claims defining protection span and patentability criteria (novelty, non-obviousness and utility/industrial application).

Another concern that the patent system is supposed to tackle is the one of innovation diffusion. Indeed, patent protection is conditional upon the disclosure of the invention’s characteristics in such a way that it should be reproducible by a PHOSITA (*Person Having Ordinary Skills In The Art*). In that sense, the system is supposed to avoid the waste of resources in “reinventing the wheel” and to incentivize competitors to “design around” existing patents (i.e. to find alternative ways of solving the same problem). Also, it allows for the innovation to spread faster once the patented invention has felt in the public domain¹² and promotes *incremental innovation*.¹³ The question of technology diffusion is closely related to that of *knowledge spillovers*. The latter translates the idea that “*the existence of technologically related research efforts of other firms may allow a given firm to achieve results with less research effort than otherwise*” (Jaffe, 1986). This is inherent to the public good nature of knowledge and constituted the basic justification of relying on patent systems. However, the famous article by Cohen and Levinthal (1989) contributed to qualify the “negative incentive effect” of spillovers and to question patent systems in such a context. The authors point out the fact that R&D, in addition to contributing to knowledge creation, can be mobilized to increase the *absorptive capacity* of firms, i.e. their ability to understand and implement ideas from others. Thus, the negative incentive effect would be overestimated as the existence of technological spillovers would, to some extent, catalyze R&D investments. Nonetheless, Jaffe et al. (2000) emphasize that if the existence

¹²In this respect, from a social point of view, patents have an advantage over lead-time and secrecy.

¹³Some studies (e.g. Bessen and Maskin, 2009) show that in such a sequential setting, the patent system may fail to provide the right incentives.

of spillovers have been evidenced for a long time, few research has been conducted to understand the channels through which knowledge flows. Based on survey data, they further evidence that data on patent citations are an acceptable proxy for communication between inventors and subsequent knowledge spillovers. In this setting, a patent system and the associated mandatory publication of inventions characteristics could exacerbate the (positive) spillover externality. Increased technology spreading may be further reached through *compulsory licensing* of technologies, that have both theoretical foundations (see e.g. [Tandon, 1982](#)) and practical applications: compulsory licensing of pharmaceutical products is provided for in the 1995 Trade-Related Aspects of Intellectual Property Rights (TRIPS) agreement. Although important and interesting, these strands of literature are beyond the scope of this thesis.¹⁴ Finally, the fact that the content of patents is public by definition makes patents a plentiful source of data that is widely relied on as supposed to reflect the inventive activity of firms or countries ([Griliches, 1990](#)).

Given the social cost of the patent system, many contributions have focused on examining empirically whether it was an efficient instrument in fulfilling its original objective of spurring innovation. [Machlup \(1958\)](#) wrote:

If we did not have a patent system, it would be irresponsible, on the basis of our present knowledge of its economic consequences, to recommend instituting one. But since we have had a patent system for a long time, it would be irresponsible, on the basis of our present knowledge, to recommend abolishing it.

This well-known quote perfectly reflects the complexity of the issue. More recently, noticeable contributions from [Boldrin and Levine \(2008, 2013\)](#) have pointed out the weaknesses of such a system to the extent of advising its abolition.¹⁵ They argue that patents are curbing innovation instead of promoting it. First, they emphasize that over the long run, the accumulation of patents undoubtedly discourages current and future inventors to enter the related markets due to constant litigation threats and the need of bargaining licenses. Furthermore, firms' *rent seeking* behaviours may exacerbate this. The idea is that firms might use patents as a mean to comfort market positions or to extract (undue?) monopoly rents.¹⁶ Such behaviours can take various forms. For instance, defensive patents are patents filed or acquired by a company to avoid litigation by being able to either (i) propose a win-win cross-licensing option, or (ii) threat potential plaintiffs with infringement of another

¹⁴The question of technology transfers will however be discussed in the next subsection as an important challenge with regards to climate justice.

¹⁵The even more recent publication of *The Case for Patents* by [Spulber \(2021\)](#) expresses a renewed interest for this issue, with an opposite point of view.

¹⁶*Preemptive patenting*, in the sense of [Gilbert and Newbery \(1982\)](#), is a good example of this.

patent. By sustaining the *patent thicket*,¹⁷ such “misuses” of patents may ultimately hamper innovation.¹⁸ More generally, this phenomenon is best known as the *tragedy of the anticommons* (Heller and Eisenberg, 1998): new (potentially socially valuable) technologies may not emerge due to disparate ownership of the required patents.¹⁹ A possible solution to this problem is the formation of a *patent pool* in which patents related to a specific technology are cross-licensed by their owners in order to facilitate the access to them and, ultimately, to foster technology development. At the beginning of the 20th century, the patent war that opposed the Wright brothers to other aviation pioneers (including Glen Curtiss) is considered to have hobbled the development of the U.S. airplane industry. In 1917, the U.S. government urged them to form a patent pool, the Manufacturer’s Aircraft Association, thus unlocking the sector and allowing for the manufacturing of airplanes to participate in the war effort (Freiwald, 2013).

An additional argument from patent critics is that there is few evidence that stronger patent protection has enhanced innovation. If anecdotal evidence such as the one of the airplane industry is useful to highlight the issues raised by the patent system, drawing general conclusions is more complex in several respects. First, the efficiency of the patent system as an innovation catalyst highly depends on the field of interest. For instance, it is well grounded that patent protection is more important in pharmaceuticals than in other sectors (see, e.g., the classic study by Mansfield, 1986).²⁰ Even in a given sector, the importance of patents as an appropriability instrument depends on the nature of inventions. Cohen et al. (2000) show for instance that patents are best suited to protect product innovation than process innovation²¹ (as an aside, lead time and secrecy appears as preferred mechanisms in both cases). Finally, firms might have different patenting strategies. The study by Arundel (2001) highlights the fact that large firms are more likely to value patent protection relative to secrecy. Second, the measurement of technical change presents important stakes. What

¹⁷Someone is said to be facing a patent thicket when producing a good requires licensing deals from many patent holders over many inventions. For instance, a smartphone is susceptible to contain around 250,000 patents according to some estimations (Yang, 2014)

¹⁸This is especially true if patent boundaries are ill-defined. This is the core of the *probabilistic patent* concept developed by Lemley and Shapiro (2005).

¹⁹The absence of cooperation between patent holders implies a *double margin* that leads to an increase in the cost of implementing the underlying technology.

²⁰In several countries, the pharmaceutical industry is subject to a special regime by which inventions may be asked for a Supplementary protection certificate that extends the lifetime of related patents. This is due to the fact that being granted a Marketing Authorization is a long process that delays the commercialization of inventions.

²¹Product innovation is supposed to either (i) open new markets or (ii) improve the characteristics of existing goods. Process innovation is supposed to lower the cost of technologies. For instance, Cohen and Klepper (1996b) consider that R&D leads to a raise in the price cost margin: product innovation allows for a greater quality that justifies charging a higher price for the underlying product, while process innovation contributes to decreasing the margin cost of production of that same good.

is the patent system supposed to increase? In the first place, it is meant to provide incentives to invest in R&D activities. R&D spending naturally appears to be the most suitable measure a patent policy evaluation should be based on. But to go further, one also wishes to appreciate whether the system allows for actual, concrete technical change. Indeed, R&D expenditures are the input of the innovation process: as such, they encompass the inherent uncertainty of the research process. To overcome this, scholars have studied the impact of patent counts or the strengthening of intellectual property rights (IPRs) on the number of inventions, total factor productivity (TFP) or patent counts themselves. This literature provides ambiguous results. Moser (2013) finds that countries with no patent system did not prove less innovative with regards to the number of innovations introduced to the 19th century World Fairs, but shows differences in the direction of innovation. Kanwar and Evenson (2003) highlight, at the country level, a positive and unambiguous relationship between R&D spending and an index of IP strength. Still with regards to R&D expenditures, Sakakibara and Branstetter (2001) evidence that Japanese firms have not been responsive to the strengthening of IP rights in 1988. Baudry and Dumont (2017) illustrate a positive correlation between patent counts and labor productivity at the country level, but which does not hold when considering total factor productivity.

A related and important question about the patent system lies in the heterogeneity in the *value* or *quality* of patented inventions. Based on this observation, researchers have highly relied on the so-called patent *metrics* to account for this heterogeneity (see Squicciarini et al., 2013, for a survey of the most common metrics). Patent “quality” is a multi-dimensional concept that still lacks a consensual definition. Patent value can be disentangled into social and private value. Social value of an innovation can be defined as in Trajtenberg (1990): “*the social benefits generated by the innovation in the form of the additional consumer surplus and the profits stemming from the innovation*”. Focusing on Commuted Tomography scanners, he derives welfare generated from the set of products available at a given year. He observes that while not correlated to simple patent counts, the welfare value is correlated with *forward citations*-weighted count of patents. The appreciation of whether a patent fulfills the patentability criteria is based on the *state of art*. If an invention builds on former knowledge, identifying and citing associated patents is helpful in assessing the novelty and inventive step of an invention. A highly cited patent is thus likely to have had an important impact in the field. The number of received citations, if corrected for *self-citations*, is independent from the patent owner and thus presents the advantage of being sheltered from potential manipulations. Conversely, private value is usually tackled by metrics the applicant has control of. For instance, Pakes (1986) relies on renewal data to assess the private value of patents. As maintaining a patent requires the payment of

a regular fee, renewal decisions are informative about the owner's expectation about the invention's returns as it reflects firm's willingness to pay for patent protection. It is worthwhile to notice that social and private value might be disconnected: for instance, a patent protecting a marginal invention (i.e. having a low social value) might present the advantage of blocking the economic development of competitors (hence having a high private value). However, distinguishing social value from private value on the basis of patent metrics may prove challenging. For instance, [Harhoff et al. \(2003\)](#) find that forward citations are positively associated with the value of patents as declared by firms themselves. In a similar vein, [Hall et al. \(2005\)](#) have shown using the Tobin's q method that the number of citations received per patent is positively related to the stock market value of firms. [Sampat and Ziedonis \(2004\)](#) proxy the "economic" value of patents by (i) the fact for a patent to be licensed and, if so, (ii) the revenue from licensing. Their results show that patent citations are good indicators of whether a patent is licensed, but not of subsequent revenue. [Abrams et al. \(2013\)](#), using data on licensing revenues from patents held by non-practising entities, evidence an inverted-U relationship between patent citations and patents' value. They argue this result is due to the fact that high-value inventions are subject to strategic patenting by incumbents to deter market entry, which translates into fewer citations.

Whereas some of them are left apart from the core of this work, all of the generic patent-related issues mentioned in this section are crucial in allowing low-carbon technologies to emerge, improve and spread. The next section discusses the place of patents in the current environmental challenges, especially in energy-related ones.

The role of patents in energy transition

It was mentioned above that environmental innovation faces a *double externality* problem. Associated research has wondered whether green technologies were in need for dedicated innovation policies. [Jaffe et al. \(2005\)](#) focus on the nexus between environmental and innovation policies and conclude that environmental policy alone, while having the side effect of providing technological advantages to clean technologies, might not be sufficient to directed research investments. The authors' arguments in that sense relate to the public good nature of the environment (that would justify specific and greater public support), the lack of actual climate policy action, the greater political acceptance of innovation policy compared to environmental policy, the dynamic character of the latter (that current policies would fail to account for) and the global nature of climate change. By contrast, [Nordhaus \(2011\)](#) defends what he calls *price fundamentalism*, i.e. the idea that once the environmental externality is perfectly corrected for (by pricing carbon), low-carbon technologies do not require any extraordinary support relative to "conventional" innovation to

emerge. However, the author himself admits that price fundamentalism only holds under a set of quite strong assumptions. Notably, it highly relies on the ability of environmental policy to set the “right” carbon price, i.e. that would fully internalize the associated environmental damages, which has been shown to face many practical hurdles.²² The work of [Acemoglu et al. \(2012\)](#) also outlines the need for an innovation policy that would favor green technologies relative to conventional ones, notably due to a *state dependence* that involves increased profitability and productivity for technologies for which the knowledge stock is larger. [Fischer and Newell \(2008\)](#) also highlight the fact that, while pricing emissions is the most effective single policy to reduce emissions, the optimal policy portfolio includes both emissions pricing instruments and green R&D subsidies. Whereas most of these studies focus on non-patent policies to encourage private R&D,²³ the patent system is at least in the background of most technological paths. For instance, the International Renewable Energy Agency ([IRENA, 2013](#)) has underlined the role of intellectual property rights in the energy transition, and especially in spurring innovation in renewable energy technologies.

Also, some authors have considered reshaping patent policies in order to tackle climate change issue. [Gerlagh et al. \(2014\)](#) extend the work by [Acemoglu et al. \(2012\)](#) and consider that patent length can be adapted to foster the development of clean technologies.²⁴ In that sense, policymakers can rely on a wider portfolio of policies: if the amount of research subsidies is fixed, patent lifetime should be adapted dynamically according to the stage of technology development. Especially, patent length should be higher at earliest stages of technology development, then decrease. Reversely, constant finite length of patents should be joint with research subsidies which amount decrease with technology development.²⁵ [Langinier and Ray Chaudhuri \(2019\)](#) examine, in the presence of emission taxation, the conditions under which reducing patenting costs and strengthening patentability criteria lead to a reduction in the emissions level. One of their result is that a for an emission tax rate above a certain threshold, introducing a patent system might lead to an increase in the emission level. This effect can be alleviated by lowering patenting cost for green

²²In such a case, it is necessary for green technologies to be especially promoted. The author argues that a possible solution in this purpose would be to extend green patents’ lifetime.

²³A patent system may be considered less flexible than, for instance, research subsidies. In practise, most of patent-related policies concern the so-called *patent box*, which consists in a preferential tax rate for revenues from licensing or transferring patents.

²⁴In their paper, [Acemoglu et al. \(2012\)](#) consider that successful inventors are rewarded with a one-year patent and that R&D subsidies are the only driver of the innovation policy.

²⁵To some extent, such an idea of increasing patent length has already been implement in the pharmaceuticals industry. Indeed, drug patents can be subject to a Supplementary protection certificate that extends maximal patent protection from 20 to 25 years in Europe. Such a measure is meant to compensate the necessary time for drugs to obtain marketing authorisation.

technologies, for instance by *fast-tracking* green patent applications.²⁶ The work of [Bonnet \(2016\)](#) is based on the idea that a *Pigovian* carbon tax is only effective in cases where the polluting good market is competitive. The author further argues that a patent system creates distortions, implying an imperfect competition framework. In this context, the regulator would need to jointly design environmental and innovation policies (resp. the taxation level and patents' length and breadth) to provide an efficient support to low-carbon innovation. Putting this into practise could however be impeded by the fact that different institutions are responsible for environmental and innovation policies. In this regard, [Choi et al. \(2022\)](#) consider a polluting industry in which a patent office manages the patent policy (i.e. sets patent length) and that an environmental agency is responsible for correcting environmental externalities by taxing emissions. They show that, in polluting industries that are not subject environmental policies, increasing the lifetime of patents may help curbing pollution. Indeed, the polluting output production by the patent holding monopolist, and associated emissions, are lower during the patent period than once the invention can be replicated by competitors. However, they show that when environmental policy applies, the optimal patent length depends on the weight that each agency assigns to environmental damage. Finally, while out of the scope of this thesis, it is worthwhile to note that patents are expected to play an important role in technology transfer ([Hall and Helmers, 2010](#)) and, subsequently, climate justice.

Beyond policy-oriented uses of patents, their use to evaluate the outcome of innovation or environmental policies is quite common. For instance, innovation studies of the wind power sector alone extensively rely on patent data to assess different aspects of the innovation process: knowledge spillovers ([Braun et al., 2010](#); [Grafström, 2018](#)), learning-by-searching ([Tang and Popp, 2016](#); [Grafström and Lindman, 2017](#); [Odam and de Vries, 2020](#)), technology transfers ([Haščič and Johnstone, 2011](#)), policy studies ([Johnstone et al., 2010](#); [Lindman and Söderholm, 2016](#); [Schleich et al., 2017](#); [Zhang et al., 2018](#); [Lin and Chen, 2019](#)), technological trajectories ([Huenteler et al., 2016](#)), technology development and market maturity ([Dubarić et al., 2011](#); [Baudry and Dumont, 2016](#)), efficiency of R&D ([Kapoor et al., 2012](#)). The use of patent counts as an indicator of “green” innovation have been fostered by the implementation in 2013 of the Cooperative Patent Classification (CPC) by the European Patent Office (EPO) and the United States Patent and Trademark Office

²⁶Some patent offices offer the possibility for clean technologies inventors to fast-track their patent applications, i.e. to ask for a more rapid examination. In addition to reducing informational asymmetries, it allows for decreasing the opportunity cost imputable to the examination process (loss of profit while examination is pending). [Dechezleprêtre \(2013\)](#) provides information about such policies and analyzes the impacts of their implementation with regards to technology diffusion.

(USPTO). Unlike the widely used International Patent Classification (IPC), the CPC allows, as it had already been recommended by the United Nations Environment Programme (UNEP, 2010), to directly identify patents related to low-carbon technologies through the Y02 class, namely “Technologies or applications for mitigation or adaptation against climate change”. Such a distinction allows for instance to analyze the direction of research toward environmental-friendly technologies. The recent publication by the International Energy Agency (IEA, 2021), jointly with the EPO, is a good example of this phenomenon. But such uses of patents face the issues mentioned earlier. Recall that there are two good reasons why patents would fail to actually reflect technical progress. First, not all inventions are patented since, in some cases, secrecy or lead time might be favoured in order to insure appropriability of R&D returns. Second, not all patented inventions have the same value for society and, even if patent counts are now usually corrected by relying on some patent-related metrics, there is few evidence that these corrected counts are correlated with actual technical change. This comes from the fact that technical change is a multidimensional concept and that some of these dimensions may not be directly measured by quantifiable metrics. At least, the required information in this purpose would be very costly to collect. Conversely, patent data is available in abundance. Indeed, in addition to the fact that patents must be publicly disclosed, patent offices aim at providing the widest access to their content.

It is thus of crucial importance to assess whether patents do accurately reflect technical change, especially in green technologies which are expected to emerge and develop to limit climate change and its consequences, and which are subject to a massive public support in this purpose.

Thesis structure and summary of the chapters

In this thesis, we question the relevance of relying on patents, both to spur and to measure innovation activity. Confronting patent data with measures of actual, concrete technical change is a useful exercise in this purpose. We focus on the use of patents by firms in the European wind power industry to assess (i) whether it is worthwhile strengthening intellectual property rights for green technologies, and (ii) whether patent data can be safely used to reflect technical change in the field. This work relies on patents filed at the EPO, that offers inventors the opportunity to protect their inventions in several countries through a unique centralized process.²⁷ Focusing on EPO patents provides several advantages. First,

²⁷At the time being, the EPO has the charge of examining patent applications and, where appropriate, granting patent protection. In such cases, patents obey the respective legislation of targeted countries. The future European *unitary patent*, that should come in force by spring 2023 in participating countries, will by contrast have a unitary effect in the whole area.

all information regarding these patents is provided in an exhaustive manner by the EPO *via* the PATSTAT database. Second, it is considered that the relevant geographical market for wind turbine manufacturers located in European countries is the European Economic Area (EEA).²⁸ In this context, one can expect important improvements to be protected at the European level. Third, supra-national patents are usually considered as especially valuable patents. Since the cost of protection increases with the number of targeted jurisdictions, applying for protection in several countries reflect the inventor's willingness-to-pay for protection and hence the expected economic spinoffs from the invention. Also, the EPO is often considered as a "*gold standard*" with regards to the quality of its examination process, that involves three examiners.²⁹

Chapter 1 focuses on the "dark side" of the patent system and tackles the issue of strategic patenting. Lanjouw and Schankerman (2001) have shown that patent disputes provide useful insights in this objective since they reflect strategies of firms to capture the *innovation rent*. In this study, we take advantage of data on patent oppositions provided by the PATSTAT database from the EPO. Opposition at the EPO allows any third party to claim a patent's invalidity within the 9 months following the latter's grant. The EPO then re-examines the underlying patent's content and has to decide between upholding, amending or revoking it. In the same vein as litigation, opposition is based on a disagreement about a particular patent between its holder and a third party. However, the decision regarding opposition applies simultaneously in all countries while litigation requires country specific settlement. It has the advantage of making data collection easier and to allow for supra-national analysis. However, amounts at stake are usually lower in an opposition procedure than in litigation cases (Mejer and van Pottelsberghe, 2012). Based on a sample of wind power-related patents filed at the EPO, we first analyze the impact of both patent and applicant characteristics on the probability and extent of opposition (the extent of opposition being the number of unique opponents to a same patent). An important result is that patents with a high private value, as proxied by their geographical scope, are more likely to face oppositions. In the second part, the analysis of the determinants of opposition outcomes are informative about the strategic character of oppositions. Indeed, "sham" oppositions may be directed toward valuable patents to delay the commercialization of associated products or to create uncertainty amongst competitors (Schneider, 2011). On the basis of beta regressions, in which the dependent variable is the share of remaining patent claims posterior to the opposition, we observe that patents with a high private value are

²⁸See for instance the European Commission M.8134 case with regards to the 2016 Siemens-Gamesa merger.

²⁹See Van Pottelsberghe (2011) for more information.

also less likely to resist oppositions. This suggests that oppositions in the wind power industry are legitimate instead of strategic and that the opposition procedure is primarily used to weed out undue patents. In addition, we propose a measure of the defensive character of patents based on the technological distance between a particular patent and its owner portfolio. Indeed, defensive blocking strategies ([Blind et al., 2009](#)) might consist in building a patent fence around an important invention in order to secure future technological space, which could ultimately hamper technology development in an even more pronounced manner (than the one of protecting one single invention). We argue that in the presence of such strategies, patents that are close to the technological core of their owner should be more likely to be opposed. However, our results do not evidence the existence of such strategies. If strategic uses of patents do not seem to be a common practise in the wind power industry, one can nevertheless wonder to what extent the increase in the number of patents went along with actual technical changes. The following chapters of the thesis are dedicated to this question. More precisely, they will focus on wind turbine (WT) manufacturers to appreciate the correlation between the number of patents held by firms and their concrete contributions to technical progress. The objective is twofold. First, it is to provide additional understanding about whether the patent system allows for such changes. Second, it is to inform about the relevance of relying on patent data as a measure of technical change. Chapter 2 is dedicated to disentangling between product innovation and process innovation based on patent information. The theoretical literature has for a long time distinguished between these two elements: product innovation is supposed to translate into technical improvements of goods while process innovation affects the cost of technologies. After retrieving the whole description of wind power patents filed at the EPO, we use text-mining techniques to measure the product and process character of patents (hereafter “productness” and “processness”, respectively). We rely on the work of [Banholzer et al. \(2019\)](#) who identified product and process-related keywords to allow for such a distinction. However, by contrast to their work, we consider that one single patent can concern both product and process innovation.³⁰ The productness (resp. processness) of a patent is given by the number of occurrences of product (process) keywords in the associated document out of the total frequency of keywords (product and process). A descriptive analysis of the dynamics of these indicators between 1990 and 2017 highlights the fact that, until the mid-2000, (patented) innovation was mostly product-oriented. If product innovation remains dominant after that, the 2004-2005 period represents a breakthrough in the orientation of

³⁰For instance, in 1880, Joseph Swan was granted a patent for a process of manufacturing incandescent light bulbs that allowed for avoiding early blackening.

innovation, process innovation beginning gaining ground from then. One possible explanation for this phenomenon relates to the type of public support to the wind power technology. We argue that promoting wind power through a *feed-in tariff* (resp. CO₂ pricing) scheme is likely to direct innovation toward process (product) innovation. The rationale for this is that under a CO₂ pricing policy, energy selling price directly depends on demand while it does not in the case of a FIT support. In a simple model, in which low wind speed is associated with a high electricity demand and reversely, wind farm developers subject to CO₂ pricing will be interested in turbines that perform well at low wind speed, at which electricity price is the greatest, which can be reached through product innovation. By contrast, under a FIT policy, they should give less attention to the production volume and be encouraged to choose cheaper machines, process innovation being the key here. Observation of the evolution of FIT support in Europe and the EU-ETS carbon price is consistent with this view. The distinction between product and process innovation, and especially “productness” and “processness” measures of patents, will be mobilised in the two following chapters.

Chapter 3 aims at confronting patent counts with objective (or at least patent-independent) measures of technical change and thus share a common objective with the work of [Trajtenberg \(1990\)](#). Wind turbine manufacturers and technical information about their machines are retrieved from THEWINDPOWER database. Product innovation is supposed to affect the electricity output of turbines, which depends on wind speed, the rotor diameter and the so-called *power coefficient*. It is considered that manufacturers only can act on the two latter, i.e. innovation leads to an increase in the power output of turbines through two channels: increasing (i) the rotor size to capture more energy from the wind, and/or (ii) the power coefficient that reflects the efficiency in the conversion of kinetic energy into electric energy. If increasing the turbine height may allow reaching higher wind speed, our objective here is to compare the performance of turbines in common wind speed conditions. The power coefficient depends on the shape of the turbine’s power curve and is computed for any given wind speed. Since we wish to observe an overall performance level, we rely on the expected annual energy production (AEP) of each turbine, which computation is based on a Rayleigh wind speed distribution associated with the power curve of each turbine. Finally, the ratio between the expected AEP and the rotor size provides an indication about the overall efficiency in the conversion process for each turbine. This indicator will be referred to as the performance of turbines. We then use frontier analysis to draw the state of art at a given period. More precisely, one turbine lies on the frontier if it allows for the highest performance level at a given rotor size. It is thus implicitly considered that improving size without sacrificing performance is challenging, which appears quite strikingly

from our data. We assess the respective contributions of WT manufacturer to technical change by observing the location of new turbines at year t relative to the $t - 1$ frontier. A manufacturer is considered to have a contribution to technical change at year t if one of its turbine entering the market at year t lies above the $t - 1$ frontier. Radial distances provide information about the extent of this contribution. Finally, we check for the relationship between patent counts and contributions of firms to technical change based on a panel of WT manufacturers over the 2000-2017 period. Our results suggest that, at the beginning of the period, improvements have been possible despite little patenting activity in the sector. However, we observe afterwards that firms having contributions to technical change are mostly those holding patents. To reduce the effect of the evolution in patenting activity, we compare firms contributions to the share of patents they hold among the whole sector's patents. We observe a positive and significant correlation between a 4-years lagged version of this indicator and contributions of firms to technical change. This suggests that there is a delay for inventions to reach the market. In addition to this, we highlight the need for considering patent portfolio size (i.e. the number of patents active at a given period) rather than patent filings when attempting to proxy technical change using patent data. Finally, the productness measure of patent appears as useful to capture firms' contributions to technical change.

Chapter 4 includes the process innovation dimension to the analysis. In a similar vein as what has been done in the previous chapter, the idea is to assess the nature of the relationship between patent counts and process innovation. In the case of wind power, what should be expected from process innovation is a decrease in the cost of turbines, which directly affects the investment cost of commissioning wind farms. The cost of turbines is the price that is charged to wind park developers, which is not directly observed. Based on information about the actual choice of a particular wind turbine by wind farm commissioners in Europe, provided by the THEWINDPOWER database, we estimate a random profit model based on [McFadden \(1974\)](#)'s random utility model. Indeed, unlike consumers choosing the alternative that provides them with the highest utility, wind park developers will choose the wind turbine that yields the greatest expected and discounted sum of net profits. The positive part of profit comes from selling electricity production on the domestic market, while the negative part includes both operation and maintenance costs and investment cost. [Sarja and Halonen \(2013\)](#) highlighted from a survey of Finnish wind power companies the main factors affecting the choice of a turbine. The latter include production volume and cost factors along with other (mostly unobserved) factors such as reliability or availability. In a very simple model, we model wind turbine choice as a function of the energy production of turbines as well as some other turbines' characteristics such as size and rated power. The

expected energy production of each turbine for each wind farm is accurately computed by taking into account the actual average wind speed at the park location. As we only observe the positive part of profit, the unobservable part of profit, i.e. not explained by differences in technical characteristics, can reflect differences in the price charged by manufacturers as well as in unobservable characteristics such as reliability or availability factors affecting the cost. The inclusion of year dummies allows one to estimate the effect of time on the probability of selecting one specific manufacturer. Confronting these estimates with process patent counts indicates that these differences may be due to differences in prices. Indeed, the evolution in the share of process patents held by manufacturers coincides with the evolution in the effect of unobservables. This suggests that, by process-innovating, firms are able to gain market share through a decrease in the price of their machines. Data on patents, when accounting for the “processness” of them, thus seem to succeed in measuring process innovation dynamics.

This thesis ultimately delivers an encouraging message with regards to the European patent system. Indeed, focusing on the European wind power industry, we show that strategic patenting is not a common practise and that the opposition procedure is mainly used in its original purpose of weeding out weak patents. We also provide evidence of a positive relationship between patent and technical change at the firm level. Especially, the evolution in contributions of firms to push the technology frontier forward, that are used to reflect product innovation, coincides with the evolution in firms’ patent portfolio size. Moreover, with regards to process innovation, the number of process patents held by firms seems to reflect differences in firms’ market share, suggesting that the latter can be explained by differences in the price charged by manufacturers. However, if patent counts can be used to reflect innovation, they have to be with caution. Especially, we emphasize the importance of considering patent portfolios instead of simple counts of patent filings as well as accounting for the time-to-market of innovations. Put together, these elements suggest that, based on observations from the wind power industry, there is no evidence that the European patent system fails in fulfilling its objective of catalyzing innovation. In this context, promoting environment-friendly technologies through a dedicated patent system remains a valid option.

* * *

Chapter 1

Use or Abuse of Patent Oppositions? Evidence from the Wind Power Industry

* * *

Critics of the patent system point to its misuse in the form of patents whose main intention is not to secure a return on investment in the exploitation of the patented invention but to extract rents without exploiting the invention. This article aims to assess the prevalence of such behaviour through the prism of patent oppositions. After arguing and substantiating from both the theoretical and the empirical literature how patent oppositions can be indicative of the existence of this type of misappropriation, the paper proposes a test based on patent oppositions at the European Patent Office in the case of the wind power industry. It focuses not only on the occurrence of oppositions but also on their outcome by proposing an original modelling of each of these two aspects. Results do not provide evidence of the use of oppositions for pure strategic motives in the wind power industry. Instead, the opposition procedure seems to be an efficient tool in correcting the first-stage examination process by the European Patent Office.

* * *

This Chapter is an adaptation of a collaboration with Marc Baudry and Béatrice Dumont.

1.1 Introduction

THE decision in 2012 of a Dallas jury in favor of General Electric in its patent dispute against Mitsubishi is often credited to have caused the downfall of the latter’s onshore wind business. Such a litigation case is not an exception in the wind power industry. According to a recent study by IntelStor (2019),¹ the industry has lost about USD 5,2 billions since 1995 due to the “weaponisation” of intellectual property rights (i.e. their use to hamper competition), these losses being mainly product sales losses.

The role of the patent system is to insure a kind of equilibrium between incentives to invest in research and development activities on the one hand, and the diffusion of the underlying protected technologies on the other hand. The diffusion of knowledge is ensured through the obligation to disclose the content of patents, which is supposed to allow anyone skilled in the art to reproduce the patented invention. The incentive purpose of the patent system is based on the attribution to an inventor of a temporary right to exclude anyone from making, using and selling its patented invention. This – temporary² – exclusivity right translates in economic terms into a market power that is conferred to the patent owner as a reward for having successfully invested in R&D. This can lead to uses of patents beyond their vocation of protection against imitation, motivated e.g. by rent-seeking behaviours. The existence of such uses might make the patent system inefficient in its original function of catalyst for progress.³

Many of these rent-seeking behaviours fall into the category of “strategic” use of patents in the sense that their main purpose is not to secure the return on R&D by preventing the imitation of the protected invention. Blind et al. (2009) emphasize that “*there is no agreed definition of strategic patenting, although most experts include the use of patents to block competitors and the use of patents in negotiations with other companies*” (Blind et al., 2009, p.2). Studies on strategic patenting usually rely on survey data (see e.g. Thumm, 2004; Blind et al., 2009) which are costly to collect in addition to be subject to a response bias. One way to avoid the latter is to get interested in patent legal disputes. In a seminal paper, Lanjouw and Schankerman (2001) emphasize that “*the frequency of court cases reflects firms’ strategies for appropriating innovation rents*” and analyze data on patent litigation. They show, among other things, that highly valuable patents are

¹<https://renewablesnow.com/news/wind-industry-has-lost-usd-52bn-to-avoidable-ip-infringements-trade-secret-theft-651619/>, consulted on November 12th, 2019.

²In his seminal paper, Nordhaus (1969a) defines patent length and breadth that provide a sufficient incentive while minimizing the social welfare loss associated with the monopoly power conferred to the patent holder.

³To the extent that some authors simply recommend the abolition of the patent system (Boldrin and Levine, 2013).

more likely to be challenged and that corporate patent owners have both lower settlement costs and strategic incentives to litigate. In the same vein, the present paper analyses patent oppositions as actions revealing potential rent-seeking behaviours belonging to the category of “strategic” use of patents. The focus is more specifically on the wind energy sector which has experienced, at least in Europe, very strong development during the last two decades both in terms of market size and in terms of patent filings, under the impetus for public policies.

The opposition procedure at the European Patent Office (EPO) allows any third-party to challenge the validity of a patent within a nine-months delay following the grant of the patent. Following this request, the patent office has to decide whether to revoke the patent, to amend it or to reject the opposition. The opposition process acts as a correction mechanism. The EPO, by deciding whether an invention is patentable or not, is the guarantor of the patent’s quality. This examination process is based on a search report that defines the state of the art related to the invention for which a protection is asked through both patent and non-patent references. [Harhoff and Reitzig \(2004\)](#) recall that patent examination is not a flawless mechanism and that relevant documents may be overlooked by office’s examiners. Thus, giving the opportunity to anyone to challenge the validity of a patent is one way of filling this gap. For instance, competitors may have more information about the given technology than the office’s examiners and can, by filing an opposition, obtain the revocation of an undue patent. The efficiency of such procedures, i.e. mechanisms that allow one to defend its Intellectual Property Rights (IPRs) and/or to challenge IPRs held by other agents may, as a corollary, impact the incentives to invest in R&D. The US Patent and Trademark Office (USPTO) implemented a similar post-grant review procedure in 2012, as suggested by [Merges \(1999\)](#), [Levin and Levin \(2002\)](#) and [Harhoff and Reitzig \(2004\)](#) in order to avoid further way more costly litigation.

Opposition, as litigation, reflects strategic interactions between firms. [Harhoff et al. \(2007\)](#) already pointed out the fact that both oppositions and settlements (to avoid patent’s re-examination), depending on their orientation and frequency, can be used for collusive or predatory purposes. [Schneider \(2011\)](#) extends the concept of “sham” or “frivolous” litigation to patent opposition. Such oppositions are filed for strategic purposes such as the establishment of a reputation for toughness, the creation or increase of uncertainty amongst industry competitors, to delay the commercialisation of an invention or to block a technological trajectory.

The existence of such strategic behaviours is of particular interest with regard to the environmental policy, in a context in which low carbon technologies are expected to replace those based on fossil resources. In the absence of a significantly more efficient instrument,

policy makers rely on patents to drive technical change toward clean technologies. First, the combination of a generic tool (i.e. that does not favor innovation towards specific technologies) such as the patent system with environmental-specific policies is supposed to translate into a directed technical change ([Acemoglu et al., 2012](#)). Thus, patent data are commonly used as an indicator to assess the efficiency of such policies,⁴ but also to proxy some other aspects of the innovation process, e.g. knowledge spillovers or cooperation in research. Second, some more marginal uses of patent as a direct policy instrument can be highlighted, as the fast-track applications for green patents, which benefit from an accelerated examination by the patent office.⁵ The International Renewable Energy Agency ([IRENA, 2013](#)) emphasizes that patents have a key role to play in accelerating the deployment of renewable energy technologies, both as a measure and a driver of the innovation process.

The wind power industry is an especially interesting sector of study for several reasons. Onshore wind power has experienced a large diffusion since the mid-1990s. This development has operated through a well-known mechanism, namely feed-in tariffs. Wind power has been one of the first clean technology that benefited from such a demand-pull policy (as early as the 1990s in Germany), which aims at creating a stable and ongoing demand and, thus, at spurring innovation (see e.g. [Baudry and Bonnet, 2019](#)). But the achievement of this goal can have a perverse effect as the monopoly rent raises for potential patent holders, making strategic behaviours even more profitable. When looking at the European wind turbine market, some interesting industrial organization issues arise. Currently, six major players share more than 90% of the market. The market tends to get more concentrated since the mid-2000s despite a relative convergence in the top players' market shares and the emergence of some noticeable Asian manufacturers. The drop in the number of wind turbine manufacturers over the same period correlates with an increased number of patent applications and grants. Nonetheless, innovation in the wind energy sector does not result solely from the R&D efforts of these market players. The wind power technology also relies on advances from a whole lot of industries and, as a consequence, there is a wide variety of firms holding patents with potential applications to the wind power industry. To illustrate that, we can notice that there are 245 different IPC 4-digits classes represented in patents recorded with at least one CPC class dedicated to wind power (Y02E 10/7). Some large, well established generalist groups compete with small, very specialized firms.

To assess the prevalence of strategic patenting through the prism of oppositions, the present paper provides an empirical analysis of the determinants of both the occurrence and the

⁴The scope goes well beyond just green innovations, and the use of patent data as a proxy for technical change has been discussed for a long time (see, e.g., [Griliches, 1990](#)).

⁵For an overview and an analysis of such policies, see [Dechezleprêtre \(2013\)](#).

outcome of patent oppositions. It substantially enriches and completes the existing literature on patent oppositions by focusing on these two facets, whereas only a few articles have dealt with opposition outcomes. It proposes a modelling of the outcome of oppositions that takes full advantage of the information available, more specifically information about the proportion of claims invalidated. The paper is organized as follows. Section 1.2 first introduces the European opposition procedure in subsection 1.2.1. Then, in subsection 1.2.2, it synthesises the existing theoretical and empirical literature before exposing in subsection 1.2.3 the contributions of the paper relative to previous opposition studies by providing some new conjectures about strategic uses of patents. Section 1.3 begins by presenting the data used in the paper as well as a global overview of patent oppositions in the European wind power sector (subsection 1.3.1). When it comes to discuss the difference between offensive and defensive patents, a more systematic approach, based on cosine distance in the technology space, than the one used in the literature is also proposed. Then, it details in subsection 1.3.2 the empirical approach used in the paper. Subsection 3.4 displays and discusses the estimation results. The different conjectures introduced in Section 1.2 are tested and an assessment of the prevalence of strategic (mis)uses of patents in the case of the wind power industry is provided. Section 1.4 concludes.

1.2 Oppositions and their determinants: an overview

1.2.1 The opposition procedure at the EPO

The European Patent Convention has 38 member states in which it is possible to file an application through a unique centralized procedure. The European Patent Office is then in charge of the examination of the applications and has to decide whether to grant a patent or not. If the patent is granted, it reaches the so-called national phase.⁶ In the very same vein, the EPO is responsible for the process of opposition filings. Any third party has a period of nine months after the publication of the grant of a patent to challenge its validity through an opposition procedure.⁷ The latter is the only way to challenge a EPO patent at the supra-national level.

From a legal point of view, three reasons can justify the filing of an opposition (European Patent Convention – Article 100): the subject-matter of one or more of the claims is not new or inventive; the patent does not disclose the invention in a manner sufficiently clear

⁶The European Patent system is not fully harmonized; once the EPO has taken the decision to grant the patent, the legislation of each targeted country applies.

⁷At the EPO, the initial publication of the patent is referred to as the A1 publication

and complete for it to be carried out by a person skilled in the art; the subject-matter extends beyond the content of the application as filed. The former and the latter elements directly refer to the breadth of the patent, in the sense that the granted patent is likely to lead to an unfounded exclusivity right, because of a too large technological scope.

In case of an opposition filing, the opposed patent is subject to re-examination by the EPO based on the content of the opposition filing. The oppositions(s)⁸ can lead to four possible outcomes:

- The opposition is prematurely stopped. This can be due both to a cancellation of the procedure by the opponent or to the lapse of the patent, without possible distinction (i);
- The patent is revoked (ii);
- The patent is amended, leading to a B2 publication (iii);
- The opposition is rejected and the opposed patent remains unchanged (iv).

Outcome (i) has to be dissociated from outcomes (ii) to (iv) because it is not a re-examination event. Nonetheless, in case of lapsed patent, the opponent has a delay of two months during which he can ask the office to re-examine the patent despite its legal death. In this case, the decision of the office must lead to outcome (ii), (iii) or (iv). In the same vein, in the case of legal death of the opponent, the office itself can decide to pursue the case.

Opposition at the EPO is not *stricto sensu* a court case, as it is settled by the EPO itself and not by some legal body. However, opposition and litigation look similar due to the fact that they both translate into a conflict between two parties surrounding an intellectual property right. As such, both parties will have to allocate resources in the defense of their own interests. According to [Mejer and van Pottelsberghe \(2012\)](#), opposition is a more affordable way than litigation: the opposition fee at the EPO is EUR 785, and total opposition costs are estimated to range between EUR 6,000 and EUR 50,000 while the cost of litigation usually involves several millions, depending on the amount at stake. This explains, at least partly, that in Europe, opposition is much more used than litigation. Moreover, the opposition procedure is subject to appeal, making it a quasi-judiciary procedure. Litigation proceedings can be divided into two categories: infringement and invalidation. Opposition and infringement cases serve different purposes: opposition happens upstream infringement in the sense that it contributes to (re)shape the patent's scope while infringement litigation consists in claiming imitation once the patent's boundaries are defined. Invalidation and

⁸It is important to note that a patent can face multiple oppositions from different opponents, but those oppositions lead to a unique decision by the EPO.

opposition are substantially the same in the sense that both of them point out the lack of novelty or inventive step of an invention.

From an econometrician point of view, the main interest of opposition lies on data considerations. First, it allows one to carry out supra-national level analysis. In the same vein as the European patent application – which is a way to ask for patent protection in a set of European countries through a unique procedure –, the office decision that follows the filing of an opposition is unique and applies in the same way in each of the targeted countries. Second, and following on the fact that the opposition division of the EPO is the oppositions’ referee, data about oppositions is systematically recorded in the office’s registers, making it easily available (e.g. *via* the PATSTAT database). By contrast, patent litigation require country-by-country court settlement. As a result, litigation data is more expensive to collect and the analysis of supra-national patents is tricky. Finally, patent litigation is the “tip of the iceberg”: in practice, most of infringement or invalidation situations lead to an amicable settlement, by means of lump sums.

Data about both opposition occurrences and opposition outcomes are recorded into the legal events table (231) of the PATSTAT database:

- 26 `event_code` are related to oppositions
 - Patents with at least a 26 `event_code` are patents that have been opposed, the number of 26 `event_code` being the same as the number of opponents. It still stands once the outcome of the case is known, but can be replaced by one of the following codes after the opposition filing;
 - Patents associated with a 26U `event_code` have faced an opposition that has been rejected on form criteria. In the CPC class corresponding to wind power turbines, only one patent is in this specific case, making any robust econometric analysis impossible. As a consequence, this particular patent opposition is neglected;
 - Patents having a 26D `event_code` have faced an opposition for which the opponent did not pay the opposition fee within the period of nine months. Here, the opposition is “deemed to not have been filed”. No patent in the sample has been affected this code;
 - Patents with a 26N `event_code` are patents that have not been opposed at the end of the nine-months period following the patent’s grant.⁹

⁹Regarding the latter point, focus has to be on patents associated with a 26X `event_code` to make sure that the absence of opposition is not due to the fact that the patent has been granted within the nine past months or due to some database update considerations.

- 27 event_codes concern opposition outcomes
 - For patents with an additional 27C event_code, the opposition procedure has been terminated due to the applicant or to the opponent, without possible distinction;
 - Patents concerned with either a 27A, 27W or 27O event_code have been re-examined by the EPO, which decided to respectively amend the patent, revoke the patent or reject the opposition. This sample includes the patents for which the opposition procedure has been terminated, but for which it has been decided to pursue the case, without possible distinction.

1.2.2 Elements of literature

This subsection proposes a review of the sparse literature, both theoretical and empirical, dealing with patent oppositions. It helps us identifying missing elements and filling these gaps by proposing a series of new conjectures to test for the presence of “strategic” behaviours.

Papers dealing with patent oppositions are summarized in Table 1.1, with a distinction between the first-step that focuses on the occurrence of oppositions and the second step that focuses on the outcome of oppositions. This section discusses intuitions, theoretical grounds and empirical handling of oppositions studies.

Reference	Sector	Period	First-step method	Second-step method	Subject matter
Van der Drift (1988)	Petroleum, agrochemicals	1978-1987	Descriptive	Descriptive	
Graham et al. (2002)	Global	1980-1997	<i>Probit</i>	<i>Multinomial Logit</i>	Determinants
Calderini and Scellato (2004)	Telecommunications	1980-2002	Descriptive	Descriptive	
Harhoff and Reitzig (2004)	Biotechnology and pharmaceuticals	1978-1996	<i>Probit</i>	-	Determinants
Schneider (2011)	Plant biotechnology	1978-2007	<i>Probit, Poisson, Zero-Inflated Poisson</i>	Descriptive	Strategic
Cincera (2011)	Global	1978-2003	<i>Probit</i>	-	Belgian applicants
Caviggioli et al. (2013)	Global	2000-2008	<i>Probit</i>	<i>Heckman probit</i>	Geographical origin
Kapoor et al. (2016)	Wind power	2001-2010	<i>Logit</i>	-	Citations
Sterlacchini (2016)	White goods	2000-2005	<i>Logit</i>	<i>Multinomial Logit</i>	Top players

Table 1.1: Summary of the literature relative to patent oppositions

Harhoff and Reitzig (2004) provide the first combined theoretical and econometric analysis of patent oppositions. In their adaptation of the model by Priest and Klein (1984), they

identify four factors that might affect the likelihood of observing an opposition: (i) diverging expectations about the outcome of the case, (ii) asymmetrical information, (iii) higher amounts at stakes (i.e. profit), and (iv) low costs of trial relative to the costs of settlement. They propose checking for the presence of these effects by assessing the impacts of some patent metrics on the probability for a patent to be opposed.

The first factor affecting the probability of opposition is the value of a patent. [Harhoff and Reitzig \(2004\)](#) show that the probability of opposition increases as the gap between the monopoly profit of the patent holder and the duopoly profit that would result from a successful opposition increases.¹⁰ This difference has to be compared to the industry profit reached in the case of settlement; the higher the monopoly profit, the less likely is the applicant to settle. In the related literature, the stake size is traditionally associated with the value of the underlying invention. Several patent metrics have been found to be correlated with patents' value: the number of forward citations (i.e. received by the patent), the number of backward citations (i.e. state of the art references) and the geographical scope (also known as family size, it reflects the applicant's willingness-to-pay for a broader protection). The hypothesis that valuable patents are more likely to be opposed seems to be empirically confirmed by [Harhoff and Reitzig \(2004\)](#) as well as other papers dealing with the subject. For instance, the number of forward citations is found to be positively associated with the probability of opposition in [Graham et al. \(2002\)](#); [Harhoff and Reitzig \(2004\)](#); [Schneider \(2011\)](#); [Cincera \(2011\)](#); [Caviggioli et al. \(2013\)](#); [Sterlacchini \(2016\)](#) and [Kapoor et al. \(2016\)](#).

[Harhoff and Reitzig \(2004\)](#) consider that asymmetries of information and diverging expectations are reflected in the complexity of inventions. In this respect, an important number of claims, a broad technological scope (i.e. a high number of IPC classes) and a longer grant lag (i.e. the time lapse between the filing of an application and the grant publication) are expected to affect the probability of opposition in a positive way. They also consider the number of X-categorized citations in the search report as a source of informational asymmetries.¹¹ In the presence of such citations, applicants have to adapt the content of their patent following the review of the examiners. Thus, X-categorized citations capture the depth of discussions between the applicant and the office's examiners during the examination process from which potential opponents are excluded.¹² The results presented by

¹⁰The model assumes that before opposition, the applicant benefits from a monopoly on its invention due to the patent protection. If an opposition occurs and ends with the patent revocation, the opponent thus has a free access to the invention, and the monopoly turns into a duopoly.

¹¹X citations are those considered to directly threaten the novelty of inventions. See the EPO [Guidelines for Examinations, Part B, Chapter X, 9.2.1](#), consulted on October 13th, 2021.

¹²Despite the fact that mandatory publications by the office provide some information to potential plaintiffs.

Harhoff and Reitzig (2004) suggest that asymmetries of information and diverging expectations play a role in the decision to oppose. Especially, the number of claims appears as an important determinant of oppositions, which is confirmed by subsequent contributions (Schneider, 2011; Cincera, 2011; Caviggioli et al., 2013; Sterlacchini, 2016; Kapoor et al., 2016).

Finally, Harhoff and Reitzig (2004) demonstrate that the probability of conflict raises as the cost of settlement relative to the total cost of trial is high. As the costs of both opposition and settlement are unobserved, Harhoff and Reitzig (2004) make the assumption that prolific patentees will be able to avoid the re-examination of their patents by offering cooperative solutions through, e.g., cross-licensing. Such behaviours are sometimes referred to as “patents as bargaining chips”. To test for this, they use the applicant’s patent portfolio size as a potential determinant of patent opposition and highlight the expected negative relationship between these two elements. Their rationale for this is twofold. First, firms with an important patenting activity are likely to be involved in repeated interactions and, as such, may be more likely to settle. Second, the stakes of opposing a patent from a large portfolio may be reduced because of a reduced relative impact. In a further contribution, Harhoff et al. (2007) warn about the fact that “*cooperation of firms to avoid re-examinations of patents constitutes a form of price fixing or collusion, albeit indirectly*”. Indeed, Calderini and Scellato (2004) have shown that oppositions in the telecommunications sector are mostly directed from incumbent firms towards newcomers while top patentees in the industry are seldom involved in oppositions against each others.

Unlike Harhoff and Reitzig (2004), Schneider (2011) finds a positive correlation between patent’s portfolio size and the probability and extent of oppositions in the plant biotechnology sector. He mentions as a possible rationale that large patent holders might be subject to “sham oppositions”, i.e. oppositions filed, despite a negative expected outcome of the case, for the purpose of e.g. deterring future entry, establishing a reputation for toughness or delaying the commercialization of a competing invention. He argues that, if such behaviours prevails, most of oppositions filings should be rejected. As these oppositions lead in most cases to a reduction in the scope of the targeted patent, he concludes that the opposition procedure is an efficient instrument in correcting the first-stage examination process rather than a strategic tool. Following this idea, Sterlacchini (2016) is the first to address the issue of “sham oppositions” using an econometric modeling of opposition outcomes. Focusing on a restricted sample of patents belonging to the top ten players of the white goods industry, he shows that patents from main manufacturers (as evidenced by European sales) are more likely to be opposed. In parallel, his results shows that these patents are more likely to be

revoked when opposed, excluding uses of oppositions for strategic purposes. The explanation they suggest for this phenomenon is that patents held by industry’s top players are more scrupulously examined by competitors, increasing the probability that a weakness in these patents is discovered.

Conjecture	Proxy	Metrics	Effect	Reference	Dep. variable
• Expected profits	Value of patents	Forward citations, family size, backward citations	+	Harhoff and Reitzig (2004)	Opposition
• Asymmetries of information, diverging expectations	Complexity of inventions	Grant lag, technological scope, number of claims	+	Harhoff and Reitzig (2004)	Opposition
• Cost of opposition relative to cost of settlement	Patents as “bargaining chips”	Patent portfolio size	-	Harhoff and Reitzig (2004),	Opposition
• Predatory purpose	Incumbency of firms		-	Calderini and Scellato (2004)	
• Geographical origin of patents		Priority publication, applicant’s country	~	Caviggioli et al. (2013)	Opposition, outcomes
• “Sham” oppositions		Patent portfolio size	+	Schneider (2011)	Opposition
		European sales	+	Sterlacchini (2016)	Opposition, outcomes
			-		

Table 1.2: Conjectures relative to patent oppositions

Other contributions mentioned in Table 1.1 address more specific issues: Caviggioli et al. (2013)’s focus is on the geographical origin of applicants while Kapoor et al. (2016) explore the categorization of citations and their effect on opposition behaviours.¹³ Table 1.2 summarizes the main conjectures that have been tested by previous contributions.

Some additional papers should be mentioned as being related to the study of patent oppositions. Burke and Reitzig (2007) analyze the consistency in the EPO’s decision making. Based on the idea that consistent decision making should lead the same patent characteristics to affect (i) the decision to grant a patent, and (ii) the decision to reject oppositions, they conclude that the EPO has not been consistent in validating biotechnology patents in the 80s. Graham and Harhoff (2014) compare U.S. patents that have been subject to litigation with their EPO equivalents and aim at anticipating the effect of the implementation of a post-grant review system following the 2011 Leahy-Smith America’s Invent Act. They show that adopting such a system would lead the U.S. to achieve important welfare gains. Harhoff et al. (2016) assess the impact of public good and patent thicket effects by analyzing the respective impacts of the concentration of patent ownership and the density of patent thickets. Their results show that an opposition (or, more generally, post-grant review) system may prove inefficient in the presence of patent thickets or highly dispersed ownership of patents. Gaessler et al. (2019) are interested in the effect of patents on cumulative innovation. For this purpose, based on a sample of opposed patents, they check whether

¹³Caviggioli et al. (2013) find that patents with a European priority are more likely to face opposition than patents with Japanese or U.S. priorities, and that patents with a U.S. (Japanese) priority are more (less) likely to be revoked when opposed. As we did not mention any specific origin in Table 1.2, the expected effect is undefined (~).

the invalidation (i.e. revocation) of a patent has led to a significantly higher number of subsequent forward citations. They find that patent revocation translates into an increase in follow-on innovation as measured by citations received by patents after the decision by the EPO about the opposition case.

1.2.3 Contributions

This section *inter alia* extends the analysis of strategic uses of oppositions to the so-called blocking strategies. Among the different patenting strategies that are criticised for diverting the patent system from its initial aim, blockade strategies have been deserved attention by several previous empirical studies.¹⁴ These studies almost systematically make a distinction between defensive *versus* offensive blocking patents, though the exact definition is somewhat confusing. Therefore, it is worthwhile explicitly wording the definition used in this paper and which derives from that proposed in [Blind et al. \(2006\)](#). A patent is said to be defensive if it is not essential for the exploitation of a technology developed by its holder, but if it allows him to secure the control of this technology *vis-à-vis* its competitors. Said another way, a defensive patent is in supernumerary but is positioned in the core of the patent holder's portfolio. Conversely, a patent is said to be offensive if it is not intended to guarantee the exclusivity of the exploitation of a technology by its holder but rather aims to hinder the development by its competitors of their own technologies. The distinction between defensive and offensive blocking patents has been made in different ways in the empirical literature. [Thumm \(2004\)](#), [Blind et al. \(2006\)](#) and latter [Blind et al. \(2009\)](#) assess the importance of the blocking motive in the decisions to patent by firms using surveys of these firms. For his part, [Sternitzke \(2013\)](#) conducts a manual, one-by-one, review of patent documents in his case study of PDE5 inhibitors in the pharmaceutical industry. By contrast, in the context of this paper, it is necessary to succeed in making the distinction between defensive and offensive patents by relying exclusively on the automatic processing of patent data. For this purpose, we rely on the notion of technological distance between patents introduced by [Jaffe \(1986\)](#) and which exploits the technological classes (in the present case, the four digits classes of the International Patent Classification – IPC) listed in the patent documents. Our method in this purpose will be developed in the next section.

In addition to those already mentioned in previous contributions, we test a set of new conjectures. This allows us to provide new insights about the potentially blocking strategic uses of the patent opposition procedure. The conjectures are summarised by topic, each

¹⁴See for instance Table 1 on page 659 of [Blind et al. \(2006\)](#) for a short list of pioneering studies that dealt with blocking patenting.

topic being generally linked to a (set of) particular patent metric(s). The numbering refers to the different topics. “A” and “B” respectively indicate that testing the conjecture relies on the analysis of the probability/extent of oppositions or outcomes of oppositions.

Conjecture 1. In the presence of “sham” oppositions, oppositions against high private value patents are more likely to be rejected.

This conjecture is based on [Schneider \(2011\)](#), who argues that the EPO should reject most of “sham” oppositions. When finding that patentees with large portfolio are more likely to be opposed in the plant biology sector, he emphasizes that these oppositions might be filed for strategic purposes and that, if so, they should be rejected in most of the cases (and the opposed patent more likely to resist). The high share of patents revoked or amended when opposed led him to conclude that strategic opposition is not a common practice, but he did not provide econometric evidence of this. In a similar vein, [Sterlacchini \(2016\)](#), focusing on the white goods top ten companies, found the amount of sales to be positively associated with the probability of opposition. To check whether oppositions toward major market players are “sham”, he assesses the impact of the amount of sales on the probability of having a particular outcome. He finds these oppositions to be more likely to lead to the revocation of the underlying patent, excluding the existence of “sham” oppositions. In both of these contributions, the concept of “sham” oppositions is related to firm size or incumbency. By contrast, we consider that any patentee may be subject to sham oppositions. [Harhoff et al. \(2007\)](#) argue that oppositions can support predation strategies in the sense that “*predatory behaviour [...] arises if an action is profitable solely because it allows the firm to exclude its rival*” and stress out that such actions may be directed toward smaller rivals. We thus propose to test this conjecture by analyzing the impact of the family size on the resilience of patents to oppositions.¹⁵

Here, unlike [Schneider \(2011\)](#) and [Sterlacchini \(2016\)](#), the core concept underlying the conjecture is patent private value. The concept of patent value deserves some comments. The concept of social value relates to the novelty of the underlying patent, as patents with high social value are impactful patents. The social impact, more specifically spillovers in favor of subsequent innovation, is typically assessed by the number of non-self citations received by a patent. Such high social value patents should not be considered as undue and are expected to be resilient to oppositions anyway. For their part, patents with a high private value are expected to have important commercial spin-offs as well, but we have no reason to believe that they are more likely to be better resilient to oppositions. For instance, a blocking (and perhaps sleeping) patent may protect a “run of the mill” and/or

¹⁵See subsection 1.3.1 for a detailed discussion of the use the family size as a proxy for the private value of patents.

unexploited invention, but may at the same time have an important impact on the market (e.g. by restricting the development of the technology by competitors). In this context, results about the impact of the private value of opposed patents might be informative about the existence of “sham” oppositions, independently from the size of applicants. Thus, if it is observed that oppositions toward highly valuable patents are more likely to be rejected, then the existence of opposition for “pure” strategic motives may be suspected (see subsection 1.2.2).

Conjecture 2. In presence of anti-competitive behaviours, oppositions are more likely to target newcomers and small firms.

Harhoff et al. (2007) point out the competition issues faced by the patent system and describe how some strategic uses of patents can translate into opposition behaviours. First, there is a risk for large companies to collude in order to avoid the re-examination of their respective patents. Such behaviour are traditionally dealt with using patent portfolio size. This can lead to cartel-like market structures and to the associated welfare losses. Second, as mentioned above, oppositions filed for predatory purposes are likely to target smaller rivals. The use of sales data or market shares in the same way as Sterlacchini (2016) is relevant in this context. However, it supposes that the “product market” and the “technology market” are identical. In the case of wind power, the final product is a wind turbine. It is possible to compute market shares of wind turbine manufacturers by relying, for instance, on installed capacities. However, it amounts to neglect all firms that are part of the wind industry “technological ecosystem” but do not produce turbines. For instance, some firms are dedicated to the production of turbine blades and compete with wind turbine manufacturers producing their own blades.¹⁶ In total, as will be developed in subsection 1.3.1, we identified 654 firms that are not wind turbine manufacturers. They were involved in about 45% of patent grants and nearly 35% of oppositions in the field. To account for this fact, we preferred using data on firms total assets as a proxy for firm size. Regressions on a sample of patents held by wind turbine manufacturers (thus including firms’ market shares instead of firms’ total assets) will be displayed in appendices as a robustness check.

Conjecture 3.a. If defensive (offensive) blocking strategies exist, then defensive (offensive) patents are more likely to be opposed.

The fact for a patent that is part of its applicant’s technological core (what we call here “defensive”) to be opposed may reveal uses of defensive blocking strategies. If the invention is well-grounded regarding patentability criteria, we should expect that patents in the technological core of their applicant will be less likely to be opposed, due to the fact that the

¹⁶See for instance, the European Commission decision on the 2017 merger between General Electric and LM Wind Power (case M.8283).

inventor has a high level of experience in the particular field of the invention. Reversely, a high number of oppositions toward such patents would reflect the fact that applicants are willing to protect marginal inventions that are just one stone in a wall blocking access to a key invention, suggesting the presence of defensive blocking strategies. In the same vein, the fact for a company to explore new technological areas (thus filing what we call here “offensive” patents) should not affect the probability of opposition if the underlying inventions are well-grounded. A higher probability of opposition for such patents would instead suggest the existence of offensive blocking strategies, in the sense that applicant’s are willing to block the development of rival technologies.

Once again, the study of opposition outcomes will be helpful to check for the prevalence of such strategies. As the positioning of potential opponents in the technological space is not directly observable by definition, we need to rely on the location of patents relative to the portfolio of opponents. This allows us to take into account the fact that a large number of firms may compete in a given, restricted technological sub-space. This is possible in the second part of the model in which we have an information about opponent parties. We emphasize that if defensive/offensive patents are more likely to be opposed, the “blocking” character of them should result in a higher probability of revocation.¹⁷ This is summarized in the following conjecture.

Conjecture 3.b. Defensive/offensive blocking patents are more likely to have their scope reduced in opposition.

The next section details the econometric models that help testing these different conjectures. In order to confirm or refute the conjectures, we use a two-steps empirical model to assess the determinants of oppositions and their outcomes. The first step focuses on the opposition likelihood and intensity (as measured by the number of opponents), while the second one concentrates on the outcomes of the procedure.

¹⁷It is not sure that blocking patents necessarily cover inventions that are less likely to be upheld in opposition. At least, observing a significant impact on the probability of having a particular outcome may signal the blocking character of patents. However, the absence of significant results does not allow us to draw strong conclusions about the prevalence of blocking strategies.

1.3 New insights on the determinants of oppositions and their outcomes

1.3.1 Data

The present paper relies on data from various databases. Data about patents were collected from the PATSTAT (Autumn 2020 version) database. The latter is useful to retrieve data on oppositions (see subsection 1.2.1) and the usual patent metrics that will serve the purpose of testing the conjectures displayed in subsection 1.2.3. Wind power related patents have been identified using the Y02E 10/7 CPC class and subclasses.¹⁸ A subsection is dedicated *infra* to explanatory variables and provides more details about data collection. We relied on the ORBIS database to collect information about the parties, i.e. applicants and opponents and on the THEWINDPOWER database for data related to the wind power industry.

Oppositions in the European wind power sector

Despite the early development of the wind power technology – enhanced in the 1980s by countries such as Denmark –, patenting activity only strikes out at the beginning of the 2000s. Since then, we observe that the industry’s actors rely massively on patent protection as evidenced by patent grants as well as oppositions. As highlighted by Figure 1.1, the number of granted wind power patents at the EPO has massively increased since the beginning of the 2000 decade. The PATSTAT Autumn 2020 database records a total of 5,282 granted patents between 1990 and 2019 in the Y02E 10/7 CPC class and subclasses. 666 patents out of the 5,282 that were granted by the EPO between 1990 and 2017 have faced at least one opposition, giving an opposition rate of 12.61% over the period. The total number of oppositions reached 981 on the 1990-2019 period. Figure 1.1 displays the evolution in the opposition rate over time.

One can observe that despite quite important variations in the opposition rate across time, the latter exhibits neither an increasing trend nor a decreasing trend. The observed increase in the number of opposition cases is mainly due to the increase in the number of granted patents. Even if the number of grants follows the massive deployment of the wind power technology worldwide and in Europe, there is no evidence that the opposition rate has reacted to the development of the market.

As mentioned above, one single patent may face several oppositions. Figure 1.2 provides an overview of the number of oppositions per wind power patent. One can notice that

¹⁸In the Cooperative Patent Classification, Y02E 10/7 class is labeled *Wind energy*. The following subclasses refer to more specific elements.

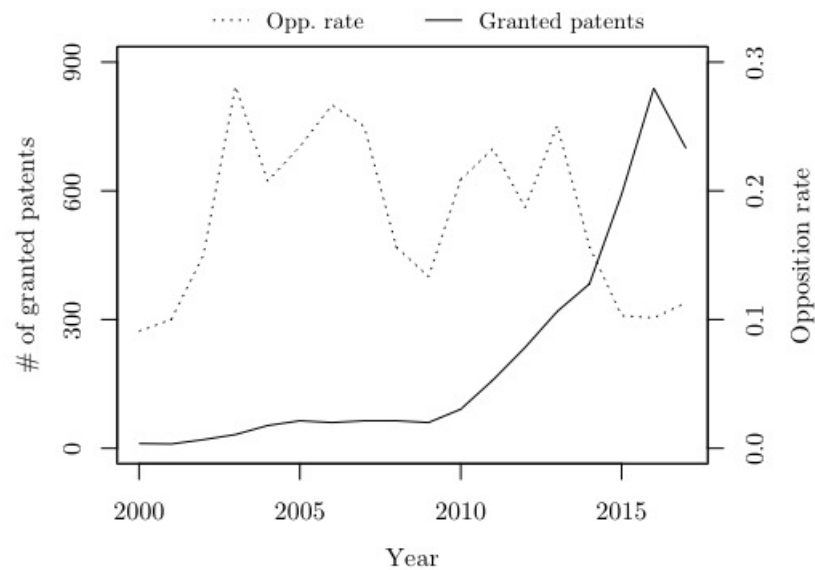


Figure 1.1: Number of installed turbines and opposed patents in the European wind power sector (cumulation), 1990-2017

– fortunately – most of patents have received no opposition. The light grey part of the graph highlights the distribution of the count of opponents within the subset of opposed patents and shows that some of these have faced up to eight simultaneous oppositions. 666 out of 5,282 granted wind power patents have faced at least one opposition (12.06%). Most of them (478) are single oppositions, but the fact for a patent to face oppositions from multiple opponents is not a rare event: for instance, respectively 123, 37 and 17 patents faced 2, 3 and 4 oppositions.

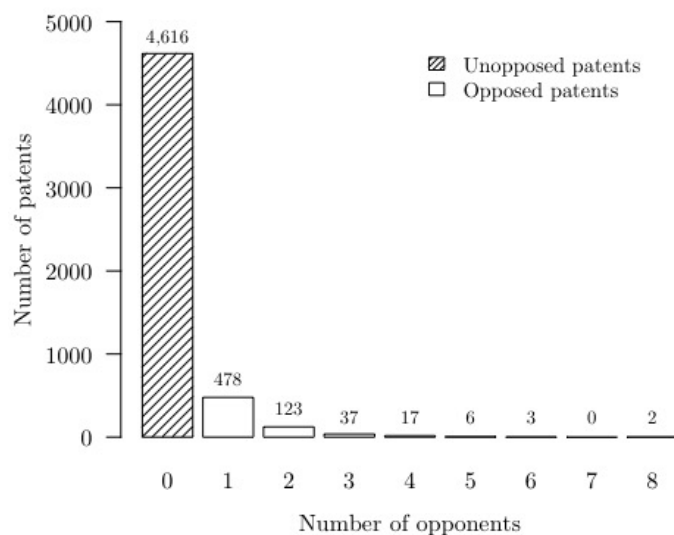


Figure 1.2: Number of oppositions per patent, 1990-2019

Figure 1.3 displays the frequencies of outcomes within the opposed patents subset. The first eye-catching observation is the number of pending oppositions: outcome is unknown in more than 50% of cases. This is a result of the relatively late use of patents by the wind power industry as outlined by Figure 1.1. The average decision lag (i.e. the time difference between the filing of the opposition and the publication of the office’s decision) ranges between 2.5 and 3 years. The higher number of oppositions on the end of the studied period explains that the outcome of some of them is not yet known. When focusing on outcomes resulting from the EPO decision, we observe that rejected oppositions are rare relative to oppositions leading to patent revocation or amendment.

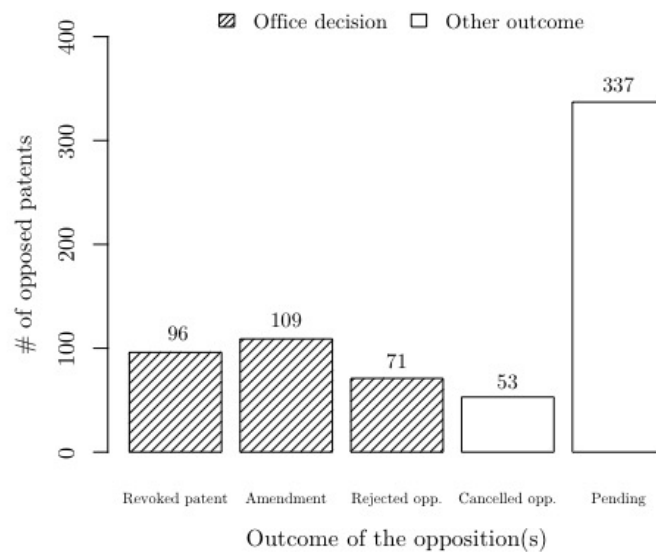


Figure 1.3: Count of opposed patents according to the outcome of the opposition procedure, 1990-2019

Digging into the distribution of opposition among firms is worthwhile for illustrating the motivation of the paper, and for easing the identification of key facets of oppositions. Table 1.3 displays the interactions of the top seven wind turbine manufacturers (Enercon, Gamesa, GE Energy, Nordex, Senvion, Siemens and Vestas),¹⁹ other wind turbine manufacturers (Other WT) and other firms (Other) in terms of oppositions. One can observe that there are differences in the behavior of firms regarding oppositions. For instance, some firms such as Enercon or Vestas seem to be particularly “aggressive”: each of them account for about 20% of all oppositions in the field. Some others appear as prime targets. For instance, Siemens, which is one of the main patent holders in the industry, has faced a total of 150

¹⁹To be considered as a “top player”, a firm must have reached 10% market share or filed more than 300 successful patents during the period. Market shares have been estimated using installed capacity data. The market we considered covers turbines commissioned by European onshore wind farms.

oppositions. Senvion holds less patents, but nearly one third of them have been opposed. GE Energy, whereas not being an active opponent, has faced a relatively high number of oppositions. Within the 2000-2019 period, it has faced approximately 3.6 oppositions per initiated opposition on average. Reversely, the German manufacturer Nordex has initiated on average 2.5 oppositions per faced opposition. There are rationales for some of these observations. For instance, GE is the only non-European manufacturer; it is mostly active in North America and has quite a low market share in Europe, which could explain this relative indifference with regard to the EPO’s opposition procedure. For other stakeholders, a micro-econometric analysis accounting for the characteristics of the parties is required. Such an analysis is provided in the next sections.

		Opponent									
		Enercon	Gamesa	GE Energy	Nordex	Senvion	Siemens	Vestas	Other WT	Other	% opposed
Applicant	Enercon		5	11	13	20	26	34	12	22	28.17%
	Gamesa	2		0	1	1	0	1	1	3	7.81%
	GE Energy	27	0		16	7	20	31	6	16	16.81%
	Nordex	6	1	2		1	5	5	5	6	17.14%
	Senvion	31	1	4	9		16	25	9	19	33.18%
	Siemens	61	0	3	7	8		51	7	23	20.20%
	Vestas	33	5	8	13	5	32		13	19	15.27%
	Other WT	17	0	4	3	1	11	18	5	15	9.06%
	Other	36	1	2	15	3	29	32	3	110	6.90%
% of opps.		21.23%	1.32%	3.44%	7.69%	4.65%	13.95%	19.92%	4.96%	22.85%	100%

Table 1.3: Matrix of oppositions between players of the wind power industry, 2000-2019

To check for the presence of strategic uses of oppositions, the analysis of oppositions’ outcomes may be relevant. Figures 1.4 and 1.5 show the outcomes of both oppositions faced and initiated by the wind turbine market top players (pending cases are excluded). We first observed that Enercon and Vestas were especially active opponents. Oppositions initiated by Enercon have been rejected in a higher proportion (nearly 30%) than the ones by Vestas (approx. 17%). [Guellec and Van Pottelsberghe \(2007\)](#) emphasize that the combination of frequent initiated oppositions and a low success rate can reflect strategic behaviours. This leads us to the introduction of what [Schneider \(2011\)](#) calls “sham” oppositions, i.e. oppositions that are filed despite a negative expected outcome of the case (for more long term purposes). The concept of “sham” oppositions is further developed *infra*. Conversely, firms that do not rely much on opposition seem to file more well-grounded oppositions as they lead in most of the cases to a reduction in the scope of the underlying patent.

A novelty from this paper is to take into account not only the outcome of the opposition proceeding, but also the extent of the amendment decision. Indeed, previous contributions have handled opposition outcomes in two ways. [Caviggioli et al. \(2013\)](#) looked at the probability of revocation and considered a binary independent variable, taking value one

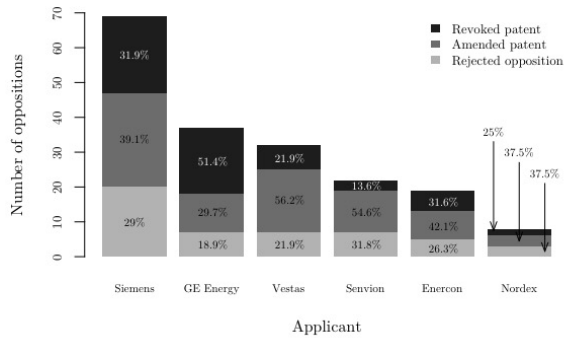


Figure 1.4: Outcomes of oppositions, by applicant (1990-2019)

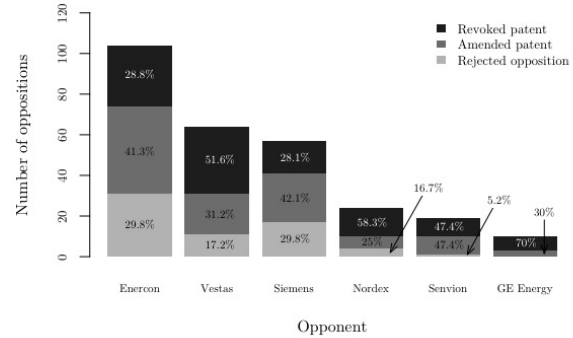


Figure 1.5: Outcomes of initiated oppositions, by opponent (1990-2019)

if the patent is revoked and zero otherwise.²⁰ Sterlacchini (2016) for his part considers opposition outcome as a multinomial response variable and merges the termination of the opposition procedure (i) and its rejection (iv) (see Section 1.2.1), so that the variable can take three different values: upheld patent, amended patent or revoked patent. Graham et al. (2002) proceeded in a similar way and included pending oppositions as an outcome as well. As discussed in Section 1.2, we made the choice to only consider outcomes that result from an office decision: revoked patent, amendment and rejection of the opposition. In our sense, the main drawback in the handling of opposition outcomes in the previous literature lies in the amendment decision. First, one has to recall that an opposition does not always target the patent as a whole, but can be limited to some of its claims. As a consequence, the “choice set” of the re-examiner may exclude complete revocation of a patent. Second, there is an heterogeneity in the amendment decision. It is key to consider the extent of amendment, that can not be carefully tackled in a discrete, e.g. multinomial setting. Finally, one has to recall that opposition may be motivated by an insufficient disclosure of the characteristics of the invention. In such cases, it may be considered that amendment does not consist in a reduction in the scope of the patent, but in a reformulation of the claims. As a consequence, the scope of the amended patent is similar to the one of the original patent.

A multinomial logit framework builds on three possible outcomes that are considered as independent. However, the different outcomes can be thought of as a graduated adjustment resulting from the new examination process. The resulting latent variable of such an ordered model can be interpreted as the resilience of the patent to the opposition it faces. The

²⁰Harhoff et al. (2003) used a similar variable as an explanatory variable for the value of patents. The dummy variable take the value zero if the outcome is successful for the opponent (patent amended or revoked) or one if the applicant prevails (inadmissible opposition or upheld patent).

approach in terms of outcomes ordered according to a degree of resilience nevertheless remains unsatisfactory insofar as an opposition does not necessarily target the patent as a whole, but may only target some of its claims. In this latter case, the decision set of the office is binary – amendment of the patent or rejection of the opposition – and, as a consequence, the amendment outcome does not necessarily constitute an intermediate alternative between the patent’s revocation and the rejection of the opposition.

We provide an attempt to address this issue by constructing an observable proxy of the resilience of patents to oppositions. The main idea is that patent amendment may lead to the removal of claims in the original patent grant document (B1 publication). As a consequence, the post-amendment publication (B2) is supposed to contain *a maxima* the same number of claims as the B1 publication.²¹ Then, the ratio of the number of deleted claims to the original number of claims reflects the lack of novelty or inventive step of the patented invention and, therefore, its legal weakness. By using the number of remaining claims instead of that of removed claims, and by considering that patents subject to rejected opposition(s) and to revocation have respectively none and all their claims deleted relative to the original grant publication, we obtain a continuous outcome variable restricted to the $[0, 1]$ interval such that the higher its value, the higher the resilience of the patent.

Accordingly, the resilience measure takes the value zero for all revoked patents and one for all unchanged patents, while it will be falling in the half-open unit interval $(0, 1]$ for amended patents (accounting for the fact that the number of claims can be the same in B1 and B2 publications). Figure 1.6 provides information about the distribution of resulting measure of resilience for patents granted between 1990 and 2019.

This figure allows one to appreciate the continuous character of the EPO’s decision regarding oppositions.

Toward an empirical analysis

In the next sub-sections, we will check for the presence of strategic behaviours by modeling patent oppositions occurrence and extent as well as opposition outcomes and “resilience” to oppositions. With this aim in view, we will consider a set of explanatory variables based on the literature on patent oppositions and outcomes (see sub-section 1.2.2). We also include some new regressors in order to check the validity of some of the conjectures mentioned in sub-section 1.2.3.

²¹The number of claims may remain unchanged despite the fact that the patent has been amended, which means that some of the claims have only been modified. A plausible rationale for this is that such oppositions are originally motivated by an insufficient disclosure of the invention’s characteristics (see Section 1.2.1).

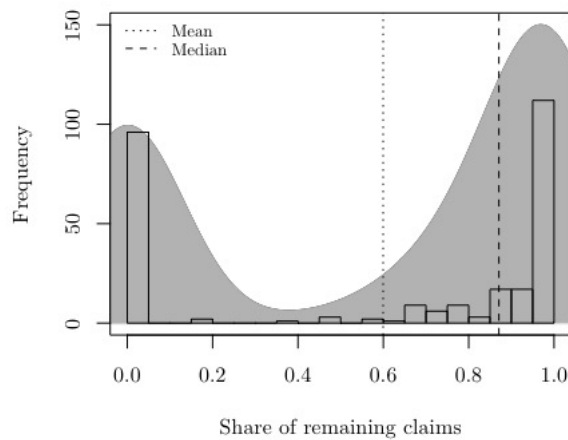


Figure 1.6: Count of opposed patents according to their resilience to opposition

The explanatory variables used in the empirical analysis are listed below and information about data collection is provided.

- The number of citations received by a patent (forward citations) is extracted from PATSTAT's table 212. As older patents are more likely to get more citations, an absolute count of citations would be irrelevant. To address this issue, a forward citation index is constructed as the ratio of the number of citations received to the average number of citations received by patents within the same cohort (i.e. the group of patents granted on the same year). Self forward citations are excluded from the count in order to make it independent from any deliberate strategy of the applicant to cite its own patents.
- As references can be added following an opposition procedure, the number of backward citations only includes the pre-opposition citations. Only the citations made by the applicant and added by the search report(s) or following third parties observations are considered.²² In PATSTAT, these elements are collected thanks to of the `citn_origin` variable in table 212.
- The number of claims only includes the claims contained in the B1 (i.e. pre-opposition) publication²³) and is used to control for the complexity of inventions. The relevant variable in PATSTAT is `publn_claims` from table 211;

²²As emphasized earlier, backward citations may be added at all different steps in the life of a patent. Here, we make sure that backward citations included during opposition proceedings are not taken into account.

²³The amendment of a patent following an opposition leads to a B2 publication, in which some claims of the original publication may have been deleted.

- The size of the applicant's patent portfolio is the count of wind power patents held by the firm at grant year. Renewals of patents are taken into account such that only patents in force (i.e. patents renewed up to the date of the opposition case and that have not reached the statutory lifespan of twenty years) are considered to be part of a firm's portfolio. It thus consists in all Y02E 10/7 patents held by a firm at a given year;
- Total assets of each firm are considered as an indicator of size. Corporate ownership data provided by the ORBIS database is used to get the relevant hierarchical level. A firm is considered as independent if none of its shareholders has more than 50% direct or indirect ownership (based on voting shares). If one shareholder is a corporate company that exceeds this threshold, then the latter's total asset is considered, and so on until finding the so-called "head of the group". Thus, it is considered that the head company controls the applicant company and thus has access to, and manage, its patent portfolio or can back the subsidiary applicant company in case of opposition. Firms' total assets were evaluated at the opposition year. This variable is used to confirm or disprove Conjecture 2.
- The family size of the patent represents its geographical scope, i.e. the number of patent offices in which protection has been requested, and is used to test Conjecture 1. Applying for patent protection at numerous different patent offices enlarges the potential geographical market but is costly. Therefore, the family size reveals the private value of the patented invention.²⁴ It is recorded in PATSTAT as the `docdb_family_size` variable from table 201.
- The technological scope of a patent consists in the number of 7-digits IPC classes in which it has been filed. This information is extracted from PATSTAT using the `ipc_class_symbol` variable from table 209 and allows us to control for patent's complexity.
- The grant lag is the number of days between the grant date and application date.
- The number of X-categorized citations is extracted from PATSTAT's table 215 using the `citn_categ` variable.
- Specialization degree: a dummy specifying whether the applicant is a wind turbine manufacturer or not. We consider manufacturers recorded into the THEWINDPOWER database to construct this variable.

²⁴for a dedicated study, see [van Zeebroeck and van Pottelsberghe \(2011\)](#)

- European applicant: a dummy that indicates whether the applicant comes from a Member State of the European Patent Convention (EPC) or not.
- The distance between the patent and its applicant's patent portfolio that is useful to test Conjecture 3.a. The distance is computed as follows. Let f_{ik} be equal to one if patent i is recorded in IPC class k , zero otherwise. Then, let f_{jk} be the fraction of firm j 's patents recorded in the same class k . The vectors f_i and f_j respectively locate patent i and firm j 's patent portfolio in a K -dimensional space. The cosine technological distance between patent i and firm j 's patent portfolio proposed by Jaffe (1986) is defined as follows

$$D_{ij} = 1 - \frac{\sum_{k=1}^K f_{ik}f_{jk}}{(\sum_{k=1}^K f_{ik}^2)^{1/2}(\sum_{k=1}^K f_{jk}^2)^{1/2}} \quad (1.1)$$

If firm j is the holder of patent i , then a small (resp. high) value of D_{ij} signals a potentially defensive (resp. offensive) patent. Conversely, if firm j is the opponent to patent i , then a small (resp. high) value of D_{ij} signals that i is a potentially offensive (resp. defensive) patent. Indeed a defensive patent is *a priori* closer to the technology core of competences of its holder, as evaluated by the cosine distance in the technology space presented *supra*, than to that of the holder's competitors. It is the opposite in the case of an offensive patent. Blind et al. (2009) find that the motive of offensive blocking is related to a higher incidence of oppositions. Said in another way, offensive patent blockade induces defensive oppositions in the sense that competitors react by challenging the attacking patent through opposition. In their study Blind et al. (2009) find no evidence of offensive opposition that would consist for competitors of a firm in filing an opposition to a defensive patent hold by this firm. This leads to Conjecture 3.a.

When modeling opposition outcomes, some opposition-specific independent variables are included in addition to those previously displayed:

- The decision lag, similarly to the grant lag, can reflect the complexity of the case. It is calculated as the number of days that separates the filing of the opposition and the publication of the office's decision;
- The number of opponents that have challenged the patent reflects a kind of "intensity" of the opposition. It is the count of 26 `event_codes` the patent records in PATSTAT's table 231 (see Section 1.2);

- Total assets of the opponent. The method is the same than the one used to determine applicants' total assets, and the variable is considered as a proxy of the size of the opponent. If the patent has faced multiple oppositions, only the larger opponent is selected;
- The distance between a patent and its opponents' portfolio, computed the same way as developed above using data on the opponent's portfolio.

In order to provide an empirical analysis of patent oppositions and outcomes, we had to use a subset of the patent population. This is mainly due to the merging of the PATSTAT and ORBIS databases. First, data provided by ORBIS starts from 2010, so that the sample used for the empirical analysis only includes patents granted at year 2010 or later. Second, due to imperfect harmonization between PATSTAT and ORBIS with regards to companies' names, some patents whose applicants or opponents could not be found in ORBIS have been dropped out. The sample we finally relied on to study patent oppositions contains 3,245 patents among which 457 were opposed. The sample used for the analysis of opposition outcomes consists in 169 patents among which 43 were upheld, 63 were amended and 63 were rejected. ORBIS has been useful to retrieve companies' total assets that are included in the models as a proxy for firms' size. By doing so, we consider that the technology market includes wind turbine specialists as well as a lot of firms having contributions, even indirect ones, to the wind technology. Based on our data, there are 654 of them which are involved in about 45% of patent grants and nearly 35% of oppositions in the field. As a robustness check, we consider in Appendices 1.A.1 and 1.A.2 a sample of patents granted to wind turbine manufacturers only. This allows us to rely on data from PATSTAT and to avoid the loss of observations associated with the matching with ORBIS. Without information about firms' size, we use instead market shares in terms of commissions wind farms equipped with models from the different manufacturers in addition to the fact that the company is a conglomerate (e.g. GE, Siemens, Mitsubishi, Hitachi).

Table 1.4 provides summary statistics for the first-step final sample and distinguishes between opposed patents and unopposed patents. On average, opposed patents have received more citations and have been filed in more countries, which could corroborate the fact that high value patents are more likely to be opposed. Opposed patents also contains more claims and have experienced a longer grant lag, which supports the fact that more complex inventions are more likely to be opposed. By contrast, we observe no difference in the mean values of the applicant's portfolio size. As such, it seems that firms holding a large set of patents are not more likely to avoid the re-examination of their patents. The fact that oppositions target larger firms on average tends, with respect to Conjecture 2, to

exclude the use of opposition for collusive purpose. To a lesser extent, patent's legal quality might affect opposition behaviours as opposed patent have, in average, a lower number of backward citations and a higher number of X-citation. For the former, it is supported by the maxima values. Consistently with [Caviggioli et al. \(2013\)](#), we also observe that, in average, patents held by European firms and wind turbine manufacturers are more likely to be opposed. Finally, when focusing on the distance measure, opposed patents seem to be less distant from their applicant's portfolio than unopposed patents, which supports the existence of defensive blocking strategies (see Conjecture 3.a).

Variable	<i>Unopposed patents</i>				<i>Opposed patents</i>			
	Mean	Std. Dev.	Min	Max	Mean	Std. Dev.	Min	Max
Forward citations index***	1.072	1.719	0	25.435	1.572	2.013	0	11.380
Backwards citations*	5.671	2.933	0	36	5.383	2.762	0	20
Number of claims**	11.874	5.096	1	66	12.575	5.589	2	43
Family size***	6.693	5.646	1	60	8.149	6.603	1	43
Technological scope	1.683	0.949	1	10	1.656	0.968	1	7
Applicant's asset*	89.672	132.948	0.001	559.349	104.765	147.095	0.001	559.349
Specialization***	0.764	0.425	0	1	0.867	0.340	0	1
Grant lag***	1,849.04	885.64	370	6,360	2,138.06	1,102.21	448	5,763
X citations*	0.924	1.540	0	13	1.061	1.606	0	8
European origin**	0.747	0.435	0	1	0.799	0.401	0	1
Distance to the applicant's portfolio	0.214	0.271	0	0.997	0.196	0.247	0	0.990
Portfolio size	191.768	184.263	1	575	191.147	169.154	1	575
Observations	2,788				457			

Note: results from t-tests on the average values of variables between opposed and unopposed patents are provided.

***, **, * indicate significant differences at, resp., the 0.1%, 1% and 5% levels.

Table 1.4: Descriptive statistics for the first-step final sample

Summary statistics for the second-step sample, displayed in Table 1.5, show no clear-cut evidence that patent's social value affect the probability of having the opposition rejected. Following the statement of Conjecture 1, this would lead us to exclude the prevalence of oppositions motivated by strategic considerations. Relying on the summary statistics of the family size (i.e. private value) leads us to the same conclusion. We observe that, on average, the office decision is longer for amended patents and that the number of claims is a little higher as well. This suggests that patents covering complex inventions are more likely to be amended when opposed. However, this is not confirmed by both the grant lag and the technological scope of patents. When focusing on the proxies of the size of the parties, we observe that, quite surprisingly, revoked patents are on average patents held by larger firms while also opposed by larger firms. The number of backward citations is on average higher (lower) for upheld (revoked) patents. Finally, it is interesting to notice that revoked patents are on average closer to the opponent's portfolio than to the applicant's portfolio. This could indicate that meddling in some firms' activity can attract their attention and translate into a negative outcome of potential oppositions. However, we observe that the

distance ratio has a higher variance in the revoked patent sub-sample: this emphasizes the need for the more careful analysis provided in Section 3.4. More specifically, each effect has to be assessed *ceteris paribus* with a proper econometric modelling rather with a univariate approach.

Variable	<i>Rejected opposition</i>				<i>Amended patent</i>				<i>Revoked patent</i>			
	Mean	S.D.	Min	Max	Mean	S.D.	Min	Max	Mean	S.D.	Min	Max
Forward citations index	2.24	2.22	0	8.24	2.11	2.27	0	9.36	2.13	2.37	0	11.18
Backward citations	6.65	3.54	1	21	6.49	2.66	2	15	5.83	2.54	1	14
Number of claims	10.84	5.17	2	30	12.91	4.15	4	22	12.16	5.60	3	27
Family size	7.44	6.31	2	32	6.44	4.08	2	31	7.91	6.21	2	36
Technological scope	1.42	0.73	1	4	1.64	0.92	1	5	1.75	1.05	1	7
Applicant's asset	95.31	141.28	0.04	555.06	98.69	131.05	0.01	539.46	147.24	181.96	0.004	555.06
Specialization	0.88	0.32	0	1	0.87	0.34	0	1	0.86	0.35	0	1
Grant lag	1,793.3	877.3	790	4,425	2,045.1	921.4	539	4,586	2,045.8	1,153.6	784	5,745
X citations	1.88	1.47	1	6	2.33	1.90	1	8	2.03	1.53	1	8
European origin	0.77	0.43	0	1	0.87	0.34	0	1	0.73	0.45	0	1
Applicant's portfolio size	127.26	115.28	1	418	158.46	130.00	1	435	139.55	135.77	1	435
Number of opponents	1.16	0.37	1	2	1.30	0.71	1	5	1.54	0.76	1	4
Decision lag	893.42	451.39	434	2,728	1,132.18	445.31	659	2,632	825.21	626.69	69	3,036
Opponent's asset	33.43	46.82	1.03	133.80	29.89	51.71	1.46	307.88	47.47	102.90	0.04	555.06
Distance ratio	1.12	0.89	0	4.50	0.90	0.86	0	6.41	1.59	3.33	0	24.84
Prob. of opposition	0.19	0.10	0.05	0.51	0.21	0.09	0.06	0.49	0.21	0.12	0.02	0.53
Observations	63				43				63			

Table 1.5: Descriptive statistics for the second-step final sample

1.3.2 Method

On the probability of opposition and opposition(s) extent

A contribution of this paper relies on proposing an original modeling of oppositions occurrence. Most of the studies mentioned *hitherto* have focused on the probability for a patent to face *at least* one opposition. Like [Schneider \(2011\)](#), we emphasize the need to take into account the extent of opposition, that can be easily proxied by the number of opponents to a same patent. This number goes up to 8 in our sample, which led us to think that this variable may contain a consequent amount of information. We propose relying on different classes of models that take into account the over-dispersion of the variable (that results from the reassuring fact that an important share of patents are not opposed at all). This gives us the opportunity to distinguish between “opposable” and “intrinsically unopposable” patents.

Several different specifications were tested for both the probability and intensity of opposition. The first model is a Probit model that focuses on the probability to face at least one opposition (in terms of the count response variable, $y = 0$ against $y > 0$). We construct a binary variable that takes the value zero if the patent has never been opposed and one if the count of opponents equals or exceeds one. The dependant variable in the following

specifications is the count of opponents. Out of the 3,245 patents recorded in our final sample, 2,788 have not been opposed at the end of the legal 9 months period. These excess zeroes can lead to an overdispersion of the data and, thus, to biased Poisson estimates. The presence of overdispersion in our final sample is confirmed by the test suggested in [Cameron and Trivedi \(1990\)](#). It causes the variance to exceed the mean, whereas the Poisson model assumes their equality. There are several ways to control for overdispersion in count data models. The first of them is to use a negative binomial regression, which allows to relax the assumption of equality between the mean and the variance.

Some additional specifications are tested. An alternative way to correct for overdispersion is to consider two-steps models known as the hurdle model ([Mullahy, 1986](#)) and the zero-inflated model ([Lambert, 1992](#)). In both cases, a specific treatment of the zeroes is proposed. In the zero-inflated model, it is assumed that the zeroes may result from one of two regimes. In a first regime, the outcome is always zero. In a second regime, the outcome is generated by a count data model. The regime is unobserved but can be modelled as a Bernoulli random variable conditional on some observable variables. In the context of patent oppositions, the first regime is associated with patents that are intrinsically “unopposable” due to the very high quality of their wording and the fact that the patented invention fully satisfies the patentability criteria. The second regime is associated with “opposable” patents. For patents falling in this category, the outcome can be positive in cases where patents faced at least one opposition, but can also be zero if the vulnerability of the patent is not discovered by potential plaintiffs or if the parties have reached a prior settlement. The hurdle model by [Mullahy \(1986\)](#) differs from Lambert’s ZIP (zero-inflated Poisson) as it distinguishes between a “participation equation” and an “intensity equation”. An individual decides whether to participate or not and, if he does, he chooses to what extent he wishes to participate: if the participation “hurdle” is crossed, it leads to a strictly positive outcome. This requires the use of a truncated count data model in the second part of the model. In the specific case of patent oppositions, “participation” could be interpreted as the fact that a patent is “opposable”, but the model then implies that “opposable” patents are opposed for sure. This property does not correctly match with patent oppositions, therefore we chose the ZIP model rather than the hurdle model.

The zero-inflated model has been extended to other count data specifications such as the negative binomial model introduced above. The ZINB model is quite similar to the ZIP model, the main difference being that the dependant variable is assumed to follow a negative binomial distribution within the group of “opposable” patents.

The Vuong test ([Vuong, 1989](#)) does not provide sufficient evidence that the zero-inflated negative binomial model should be preferred to the original negative binomial model for

our data set. However, the ZINB model seems to be the more suitable to our data, as evidenced by the AIC measure. Thus, estimates will be displayed for both kind of models and compared to check the robustness of the results.

On opposition outcomes and the resilience of patents to oppositions

The econometric analysis of proportion response variables has been widely discussed.²⁵ The main issue about it is the way to tackle both 0 and 1 values. One of the most commonly used specification for proportion analysis is the beta regression proposed by [Ferrari and Cribari-Neto \(2004\)](#) in which the response variable is initially supposed to be beta distributed. The model makes it possible to directly assess the impact of some covariates on the expected resilience level.

As the beta distribution is restricted to the $(0, 1)$ open interval and even if its two shape parameters allow one to fit a broad range of distributions, it does not seem to be the most adapted method since in the present case the response variable takes zero and one values that are excluded from the distribution. Our first attempt to model the post-opposition proportion of remaining claims consists in using the transformation suggested by [Smithson and Verkuilen \(2006\)](#) and recommended by [Cribari-Neto and Zeileis \(2010\)](#):

$$y^* = \frac{y \times (N - 1) + 0.5}{N} \quad (1.2)$$

with N standing for the sample size. Using such a transformation, if $y = 0$ (resp. $y = 1$), then y^* takes a value close to but greater (lower) than zero (one). Once done, it is possible to use the “conventional” beta regression on the transformed variable that lies within the $(0, 1)$ open interval.

A relevant alternative is the zero-one inflated beta (ZOIB) regression that originates in the work of [Ospina and Ferrari \(2010\)](#). In addition to allowing the response variable to take values zero and one, it takes into account the fact that there is an over-representation of such values (which looks obvious from Figure 1.6). Similarly to the zero-inflated model used in the previous part of the model, three different processes are assumed to govern the probabilities for the response variable to take the exact value 0 and the exact value 1, as well as the parameters of the fitted beta distribution for observations falling within the $(0, 1)$ interval. Thus, an additional motivation to the use of a ZOIB model is the fact that either the zero, one and intermediate values correspond to different outcomes, respectively revoked patents, upheld patents and (most of) amended patents.²⁶ This amounts to considering that

²⁵For a discussion on proportion data modeling, see [Baum \(2008\)](#).

²⁶It was mentioned earlier that post-amendment publication may have the same number of claims as pre-opposition publication, opening up the possibility for an amended patent to have a resilience value of one. Assuming that such a specific case is originally motivated by an insufficient disclosure of the characteristics

patents with a resilience value of zero or one have been subject to a discrete choice while considering a continuum of possible decisions between these two polar cases.

1.3.3 Estimation and results

Determinants of oppositions

Table 1.6 provides the estimation results for the different specifications of the model dealing with the determinants of oppositions. Model (1) focuses on the probability for a patent to face at least one opposition, independently from the number of opponents, when model (2) estimates the effect of the independent variables on the intensity of opposition, i.e. the count of opponents. Models (3) and (4) allow for the distinction between the impact of explanatory variables on the probability of being a “certain zero”, i.e. an “unopposable” patent, and the “intensity” of opposition within the category of “opposable” patents.

Our results are consistent with most of previous findings (a recap is presented in Table 3.2.1). First, we show that proxies of both social and private value affect opposition behaviours in a positive way. The forward citations index is negatively associated with the probability of falling in the “unopposable” category while the family size mainly affects the number of opponents for patents belonging to the “opposable” category.

With regards to the use of forward citations as a proxy for patent social value, one potential limitation of this paper comes from the results highlighted by Galasso and Schankerman (2015) and Gaessler et al. (2019). Indeed, they have shown that follow-on innovation depends on patent invalidation. Their results show that invalidation is associated with an increase in the number of subsequent citations to the underlying patent. They emphasize that the impact of invalidation is heterogeneous, notably among technology fields. The forward citations index we use in this paper is computed on the basis of all citations that a patent has received. Thus, there is a risk of endogeneity. This could be corrected by using a proper instrument that would affect the count of forward citations while not directly having an impact the probability of opposition nor the resilience of patents to oppositions. Finding such an instrument is not an easy task here as the usual proxies for patent’s value (family size, grant lag, number of claims...) have been shown to be correlated to the probability of opposition. However, this risk seems to be limited in our context. Indeed, a large majority of patents in our sample have not received any citation after the publication by the office of its decision. A rationale for this phenomenon is that our focus is on patents that have been granted quite recently. The earlier year of publication of the office decision with regards

of the invention, one can consider the underlying patent to be resilient in the sense that it fulfills the criteria of novelty and inventive step.

to oppositions is 2013 and nearly half of the cases in our sample have been settled in 2018 and 2019. This little hindsight makes us think that the effect of invalidation on follow-on innovation should be quite weak. For this reason, we decided to stick with the original model and proceed the same way as done in previous opposition studies.

The result regarding the number of backward citations contradicts previous findings. Indeed, we find a negative correlation between this metric and the probability of opposition. This suggests that the number of prior art references reflects patent's legal quality rather than being a proxy of patent's value. Providing an exhaustive description of the state of art seems to shelter patents against oppositions. Second, the complexity of the underlying invention also appears as a driver of oppositions. Especially, the number of claims negatively impacts the probability that a patent falls into the "unopposable" category, while the grant lag affects the count of opponents. Still in line with previous results, technological scope do not seem to have any particular impact. We observe that the number of X-citations positively affects the probability of opposition and the count of opponents for patents belonging to "opposable" category. This result is similar to the one by [Harhoff and Reitzig \(2004\)](#). [Kapoor et al. \(2016\)](#) focused on the relationship between patent citations and oppositions in the wind power industry and which, despite expecting a positive effect of the number of X references on the probability of opposition, found it to be non-significant. A possible explanation for this is that their sample consisted in 1,094 patents filed between 2001 and 2010 and recorded in the April 2015 version of PATSTAT. One can observe from [Figure 1.1](#) that the number of patent grants strongly increased since then. This increasing technological competition may foster the overlapping of patents and make oppositions more likely and numerous. In the light of the effect of the number of backward citations, the number of X-citations may also be considered as reflecting patents' legal weakness. Finally, like [Caviggioli et al. \(2013\)](#), we observe that patents from European applicants are more likely to be opposed, suggesting that European competitors are subject to a more scrupulous monitoring.

Unlike most of previous studies, we do not observe that patents parts of large portfolios are less likely to be opposed. Patent portfolio size even appears to significantly and positively affect the number of opponents in the ZINB model. [Schneider \(2011\)](#) found a similar result in the biotechnology sector and argued this was due to peculiarities of this industry. In the case of wind power, it is more likely to be due to the repeated interactions between the top players of the industry, that account for a large part of patent filings and oppositions (see [Table 1.3](#)). This result is consistent with the fact that, based on a patent independent measure of firms' size, patents held by large companies seem to be more likely to be opposed. Indeed, applicant's total assets is found to be positively associated with the probability of

opposition in models (1) and (4). This is reassuring about uses of patents for collusive purposes evoked in Harhoff et al. (2007) and allows us to refute Conjecture 2.

	<i>Dependent variable:</i>					
	Opposition		Count of opponents			
	<i>Probit</i>	<i>Negative binomial</i>	<i>Zero-Inflated Poisson</i>		<i>Zero-Inflated Negative binomial</i>	
			Binary	Count	Binary	Count
	(1)	(2)	(3)		(4)	
Forward citations index	0.099*** (0.014)	0.152*** (0.022)	−0.404*** (0.120)	0.015 (0.030)	−0.915*** (0.284)	0.062** (0.029)
Number of backward citations (<i>log</i>)	−0.167** (0.069)	−0.305*** (0.113)	0.077 (0.290)	−0.302* (0.155)	−0.023 (0.500)	−0.319** (0.147)
Number of claims (<i>log</i>)	0.140** (0.064)	0.158 (0.104)	−1.116*** (0.266)	−0.462*** (0.141)	−1.507*** (0.387)	−0.255 (0.163)
Family size (<i>log</i>)	0.306*** (0.054)	0.532*** (0.088)	−0.304 (0.276)	0.392*** (0.151)	0.017 (0.390)	0.587*** (0.133)
Technological scope (<i>log</i>)	−0.044 (0.068)	−0.077 (0.115)	0.197 (0.302)	0.008 (0.168)	1.197 (0.749)	0.131 (0.150)
Applicant's total assets (<i>log</i>)	0.027* (0.014)	0.029 (0.024)	−0.180* (0.109)	−0.071 (0.055)	−0.313* (0.177)	−0.057 (0.041)
Specialization (<i>dummy</i>)	0.095 (0.128)	0.205 (0.221)	−0.641 (0.677)	−0.170 (0.372)	−2.167* (1.231)	−0.360 (0.295)
Grant lag (<i>log</i>)	0.366*** (0.070)	0.664*** (0.115)	−0.478 (0.304)	0.407** (0.160)	−0.715 (0.435)	0.477*** (0.141)
Number of X citations (<i>log</i>)	0.150*** (0.048)	0.277*** (0.080)	0.126 (0.219)	0.341*** (0.117)	0.411 (0.339)	0.380*** (0.110)
European origin (<i>dummy</i>)	0.216*** (0.083)	0.293** (0.141)	−0.740 (0.457)	−0.053 (0.236)	−1.349* (0.754)	0.036 (0.196)
Distance to the applicant's portfolio	−0.283** (0.125)	−0.396* (0.214)	0.457 (0.680)	−0.162 (0.381)	−2.391 (2.051)	−0.754*** (0.269)
Applicant's patent portfolio size (<i>log</i>)	0.043 (0.030)	0.075 (0.051)	0.167 (0.245)	0.168 (0.117)	0.649 (0.459)	0.217*** (0.079)
Intercept	−5.026*** (0.618)	−7.904*** (0.993)	10.869*** (2.525)	−1.337** (1.285)	14.352*** (3.883)	−3.410** (1.346)
Observations	3,245	3,245	3,245		3,245	
Year fixed effects	Yes	Yes	Yes		Yes	
AIC	2,405.2	3,110.6	3,011.1		3,095.69	
θ	-	0.714 (0.11)	-	-	-	-
$\log(\theta)$	-	-	-	-	-	0.445 (0.303)

Note:

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

Table 1.6: Probit (1), negative binomial (2), zero-inflated Poisson (3) and zero-inflated negative binomial (4) specifications for opposition likelihood (1) and opponents count (2, 3, 4)

Finally, the distance that separates a patent from the applicant's portfolio is found to have a negative impact on the probability for the patent to be opposed, as well as a positive impact on the probability for it to belong to the “unopposable” category. Patents that are close to the applicant's portfolio are more likely to be opposed. Following the interpretation

by [Blind et al. \(2009\)](#), this suggests the presence of defensive blocking strategies in the wind power sector. Firms are willing to block access to their key technologies by building a patent fence around them; nonetheless, the quite high level of uncertainty surrounding this specific estimate mitigates this conclusion related to Conjecture 3.a. Results about outcomes of oppositions may be helpful in clarifying this.

Appendix 1.A.1 shows that these findings are robust when considering the population of patents granted to wind turbine manufacturers only. Proceeding this way has allowed us to avoid the matching with the ORBIS database. Instead of using applicant's total assets, we used data on market shares on the European onshore wind power market (estimated from the THEWINDPOWER database) as well as a dummy variable indicating whether the applicant is a conglomerate or not. The insignificant impact of market share in these models is consistent with the idea that wind industry actors do not act collusively.

Topic of conjecture	Proxies	Validated
Amounts at stake	Foward citations, family size	✓
Complexity of inventions	Grant lag, # of claims	✓
Patents as bargaining chips	Applicant's portfolio size	✗
European origin	EP applicant dummy	✓

Table 1.7: Confirmation of previous conjectures

Determinants of opposition outcomes

For robustness considerations, a variable selection method is used. Table 1.8 displays results from different specifications. Models (1) and (2) follows previous contributions in modeling opposition outcomes in a dichotomous way ([Caviggioli et al., 2013](#)). Model (1) is interested in the probability of rejected opposition or amendment *versus* revocation while model (2) is interested in the probability of rejected opposition *versus* amendment or revocation. Model (1) is an ordinal *logit* regression in which outcomes are ordered from patent revocation (no resilience to opposition) to rejected opposition (total resilience), amendment being the intermediate outcome. We are interested in assessing the impact of the covariates on a latent variable reflecting the resilience of opposed patents to opposition(s). Previous contributions ([Sterlacchini, 2016](#); [Graham et al., 2002](#)) have considered a traditional multinomial *logit*. For reasons mentioned in sub-section 1.3.2, we prefer to consider outcomes from patent oppositions as ordered. Finally, a beta regression on the [Smithson and Verkuilen \(2006\)](#) transformed variable is proposed. In this model (1), we fully exploit EPO's data by using the share of remaining claims in post-opposition publications as a proxy for the resilience of patents to oppositions. For the sake of parsimony and given the number of observations,

we provide results from a stepwise version of each model in order to highlight the main determinants of resilience. All variables mentioned in sub-section 1.3.1 were considered at the beginning of the process. We finally included the probability for each patent to be opposed as an explanatory variable to control for a possible selection bias.

	<i>Probit</i>		Ordinal <i>logit</i>	<i>Beta</i>
	(1)	(2)	(3)	(4)
Decision lag (<i>log</i>)	0.2822*** (0.058)		0.8370*** (0.291)	0.5630*** (0.178)
Number of opponents (<i>log</i>)	−0.2931*** (0.089)	−0.1912** (0.088)	−1.3852*** (0.430)	−0.6378** (0.277)
European origin (<i>dummy</i>)	0.1888** (0.083)		0.6595 (0.415)	0.4464* (0.259)
Family size (<i>log</i>)	−0.1680* (0.078)			−0.3410 (0.238)
Distance to the applicant's portfolio	−0.3237** (0.135)		−1.4362** (0.678)	
Number of claims (<i>log</i>)		−0.1612** (0.076)	−0.6849* (0.392)	
Technological scope (<i>log</i>)		−0.1248* (0.072)		
Probability of opposition	0.3210 (0.387)	0.157 (0.338)	0.0821 (1.574)	0.092 (1.162)
Intercept	−1.0433** (0.407)	0.6974*** (0.177)		−3.2958*** (1.229)
Akaike Inf. Criterion	202.07	198.24	354.06	−560.41
Pseudo- R^2	0.2048	0.0626	0.0772	0.1054
Observations			169	

Note:

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

Probit (1): Opposition rejected or amendment *vs* revocation

Probit (2): Opposition rejected *vs* amendment or revocation

Table 1.8: Estimates for stepwise probit, ordered logit and beta regressions

What we first observe is the difference in the results between model (1) and (2), that differs on whether to consider the amendment outcome to be positive for the patentee (model (1)) or the opponent (model (2)). Among seven variables, only one of them appears as a determinant of outcomes in both models. These differences suggest that the amendment outcome should be tackled as a distinct outcome.

A first finding is the fact that the number of opponents to a same patent negatively affects its resilience to opposition. While trivial, this result is a positive signal about the consistency of the model. A similar result was highlighted by Caviggioli et al. (2013). We also observe

that the time lag between the filing of the opposition and the office decision has a positive impact on the resilience of patents to oppositions and that revocation decisions take less time relative to amendment and rejection decisions.

The observed impact of the private value of patents on their resilience to opposition leads us to conclude that “sham” oppositions are not a common practice in the wind power industry (Conjecture 1). Recall that the family size is the sole “pure” proxy of patents’ private value as it reflects the applicant’s willingness-to-pay for patent protection. Since this variable was found to have a positive impact on the probability and intensity of oppositions in the first place, the existence of “sham” oppositions should translate into a higher probability for them to be rejected. [Schneider \(2011\)](#) emphasizes that such oppositions can be filed despite a negative expected outcome of the case. It makes sense that a potential opponent may be tempted to use such a stratagem for the purpose of e.g. delaying the commercialization of a (valuable) invention or avoiding market share losses. Yet, conversely, patents with a large family size seem to be less resilient to oppositions. Thus, it seems that oppositions directed towards highly valuable patents are more likely to lead to a reduction in their scope, indicating that they are mostly non strategic. Even if we observe from [Appendix 1.A.2](#) that the family size does not appear as a determinant of patents’ resilience to oppositions when focusing on oppositions between wind turbine manufacturers, there is no evidence that oppositions towards high value patents are more likely to be rejected and that oppositions are used for “pure” strategic motives. This leads us to refute Conjecture 1.

Finally, it is worthwhile noticing the effect of the distance variable on the resilience of patents to oppositions. We observe that the distance of a patent from its applicant’s portfolio has a negative impact on the resilience of opposition in model (1) as well as in model (3). Once again, this suggests that strategic patenting is not a common practice in the wind power industry. In the first place, we found little evidence that patents filed close to their applicant’s portfolio were more likely to be opposed. This drew our attention to strategies of patent fencing by which firms aim at blocking access to their technologies. However, it seems that such patents are sound enough to resist oppositions. As a consequence, there is no evidence for the presence of defensive blocking strategies. Regressions from [Appendix 1.A.2](#) lead to the same conclusion as the distance measure is found to have a negative impact in model (2), (3) and (4). In parallel, the distance of a patent to the opponent’s portfolio never appears as a variable with a significant impact the variable selection method. We conclude that data on oppositions in the wind power industry do not support Conjecture 3.b.

Unlike [Caviggioli et al. \(2013\)](#), we observe that patents from European firms are more likely to be resilient to oppositions. A plausible rationale for this would be that European firms have an advantage in defending their “domestic” patents relative to non-European firms.

However, this finding can be questioned. Finally, the decision lag (i.e. the time difference between the filing of an opposition and the decision by the office) seems to affect positively the share of remaining claims.

Table 1.9 focuses on results from the zero-one inflated beta regression. In order to make the model more parsimonious as well as for computational issues, we used the so-called best subsets method that constrains to 10 the number of parameters to be estimated. Table 1.9 displays estimates for the best model according to the AIC criterion (model (5)). This model has been re-estimated in order to include the probability of opposition to avoid selection bias. Based on the different combinations of variables, some 1,700,000 models were inferred in R using maximum likelihood techniques.

It is worthwhile reminding the interpretation of the different components of the model:

- Results in the ν section provide information about the effect of independent variables on the probability of revocation against the probability of amendment;
- Impacts on μ are those on the number of remaining claims in cases of amendment, when opposition is originally motivated by a lack of novelty or inventive step of the invention;
- τ is the probability of getting the opposition rejected – or of amendment when opposition is originally motivated by an insufficient disclosure of the invention’s characteristics – *versus* the probability of amendment.

What we observe is that the complexity of the case negatively affects the relative probability of having one of the extreme values of remaining claims. When compared with the findings of models from Table 1.8, we observe that the decision lag variable does not affect the share of remaining claims anymore, but it impacts the decision to reduce the scope of the patent. This supports the idea that an amendment decision takes longer than a categorical “yes or no” decision. On another hand, the number of opponents to a same patent is shown to impact the probability of patent revocation, but not the one of the opposition being rejected (relative to amendment). Despite not being key to our purpose, these results highlight the relevance of relying on inflated-type models to study the resilience of patents to oppositions as they take advantage of the mixed (discrete/continuous) character of the resilience measure.

The results from the ZOIB specification also highlight a positive impact of the number of X-citations on the share of remaining claims in the amended publication of patents. This finding is quite surprising as the number of citations may be seen as a proxy for the patent legal weakness. As such and as emphasized in Section 1.2.2, one would expect that variable

Zero-one inflated beta (5)			
	ν $y = 0$	μ $y \in (0, 1)$	τ $y = 1$
Number of opponents	1.4866*** (0.4910)		
Decision lag	-2.0281*** (0.4791)		-0.8081* (0.4317)
Family size		-0.4500* (0.2346)	
Number of X-citations		0.5391*** (0.1515)	
Technological scope			-0.5603 (0.3763)
Probability of opposition	-1.2457 (2.0158)	-2.5832** (1.1883)	-1.8474 (1.9397)
Intercept	13.971*** (3.2910)	2.1208*** (0.3912)	6.3317** (3.0127)
Observations		169	
AIC		286.2604	
Pseudo- R^2		0.2608	

Note: * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$

Table 1.9: Zero-one inflated beta regressions for resilience to opposition

to have a negative impact on the resilience to opposition. One possible explanation is that the examination process by the EPO – and more specifically the search report – contributes to patent’s legal quality. In this interpretation, the fact for the office to grant a patent despite a high number of X citations in the first place makes the “reviewed” patent stronger (i.e. more likely to be resilient to oppositions) than patents having experienced a less tough search report. This suggests the importance of the search report in the examination process and, broadly speaking, in the ability for patent offices to grant quality patents.

Regarding Conjecture 1, we observe that the private value of patents, as reflected by family size, neither affects the probability of having the patent revoked nor the probability of having the opposition rejected relative to the probability of amendment. However, we observe that this variable has a negative impact on the share of remaining claims in cases of amendment. This tends to support results from model (1) and lead us to conclude that oppositions toward highly valuable patents are mostly legitimate.

The ZOIB specification does not highlight the distance measure as a main determinant of resilience. As a consequence, and based on models (1) and (3), we can safely conclude that if

defensive patents are more likely to be opposed, defensive blocking strategies do not prevail as these patents are more likely to get their scope reduced when opposed (Conjecture 3.b is rejected).

1.4 Conclusion

This paper analyzes the determinants of patent oppositions and of their outcomes in the wind power industry. To the best of our knowledge, it is the first one that considers the extent of scope reduction in cases of amendment. Relying on inflated type models allows us to consider the share of remaining claims as a continuous variable while taking into account the discrete character of the polar decisions (i.e. revocation of the patent *versus* rejection of the opposition). We emphasize that proceeding this way may provide useful insights for future research.

Results from this two-step empirical analysis do not provide evidence of strategic uses of the patent opposition procedure in the wind power industry. In a quite large part of the cases, the opposition leads to a reduction in the scope of the underlying patent, suggesting that oppositions are legitimate instead of strategic.

Whereas both socially and privately valuable patents are more likely to be opposed, “sham” opposition is not a common practice as these particular oppositions do not prove to be more likely rejected. On the contrary, patents with a high private value seem to be less resilient to oppositions. This indicates that oppositions towards high-value patents are legitimate instead of strategic.

We introduced a distance measure that reflects whether a particular patent is part of the technological core of the firm or whether reflects the ambition of firms to explore new technological fields. The finding according to which patents that are part of the technological core of firms are more likely to be opposed may suggest the existence of defensive blocking strategies. The existence of such strategies could hamper the diffusion of knowledge and make the patent system inefficient in this regard. However, we do not provide evidence for this. Reversely, it seems that defensive patents are more likely to have their scope reduced in opposition. This indicates that there is no generalized willingness of firms to block access to their technologies by filing lousy patents around.

Finally, our results suggest rather sound uses of oppositions in the wind power sector. The opposition procedure seems to be an efficient tool in its original aim of correcting the first-stage examination process and weeding out lousy patents.

Appendices of Chapter 1

Appendix 1.A Robustness

1.A.1 First step

	<i>Dependent variable:</i>	
	Opposition	Count of opponents
	<i>Probit</i>	<i>Negative binomial</i>
Forward citations index	0.075*** (0.019)	0.099*** (0.028)
Number of backward citations (<i>log</i>)	−0.189** (0.090)	−0.322** (0.138)
Number of claims (<i>log</i>)	0.204** (0.082)	0.157 (0.123)
Family size (<i>log</i>)	0.229*** (0.070)	0.367*** (0.109)
Technological scope (<i>log</i>)	−0.056 (0.085)	−0.108 (0.136)
Market share	−0.961 (0.668)	−1.793 (1.070)
Grant lag (<i>log</i>)	0.514*** (0.084)	0.850*** (0.130)
Number of X citations (<i>log</i>)	0.214*** (0.059)	0.314*** (0.092)
European origin (<i>dummy</i>)	0.262** (0.111)	0.417** (0.176)
Distance to the applicant's portfolio	−0.178 (0.141)	−0.414* (0.234)
Applicant's patent portfolio size (<i>log</i>)	0.121* (0.066)	0.214* (0.108)
Conglomerate (<i>dummy</i>)	0.085 (0.141)	0.101 (0.222)
Intercept	−6.084*** (0.767)	−9.161*** (1.169)
Observations		2,018
Year fixed effects	Yes	Yes
AIC	1,667.9	2,161.6
Pseudo- R^2	0.0962	0.0788
θ	-	1.042 (0.235)
<i>Note:</i> * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$		

Table 1.A.1: Probit and negative binomial specifications for resp. opposition likelihood and opponents count. Data: population of patents granted to wind turbine manufacturers.

1.A.2 Second step

	<i>Probit</i>		Ordinal <i>logit</i>	<i>Beta</i>
	(1)	(2)		
Decision lag (<i>log</i>)	0.1336** (0.067)			
Number of opponents (<i>log</i>)	−0.3539*** (0.069)	−0.2672*** (0.059)	−1.6098*** (0.316)	−0.8706*** (0.203)
European origin (<i>dummy</i>)	0.2329*** (0.071)	0.1035* (0.063)	1.1049*** (0.334)	0.5346** (0.212)
Distance to the applicant's portfolio	−0.3081*** (0.104)		−1.1703** (0.473)	−0.8176*** (0.313)
Number of claims (<i>log</i>)	−0.1068** (0.051)	−0.1623*** (0.045)	−0.8465*** (0.235)	−0.3049* (0.150)
Portfolio size (<i>log</i>)	0.0583** (0.024)		0.1668 (0.106)	0.1193* (0.071)
Number of X-citations (<i>log</i>)		−0.0598 (0.037)		
Probability of opposition	0.1324 (0.216)	0.0683 (0.171)	0.8524 (0.827)	0.5897 (0.569)
Intercept	−0.4883 (0.525)	0.6358*** (0.120)		−0.716 (0.572)
Akaike Inf. Criterion	337.66	270.69	532.14	−1,168.04
Pseudo- R^2	0.1413	0.1184	0.0968	0.1990
Observations			267	

Note:

* $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$ *Probit* (1): Opposition rejected or amendment *vs* revocation*Probit* (2): Opposition rejected *vs* amendment or revocation

Table 1.A.2: Estimates for stepwise probit, ordered logit and beta regressions. Data: sample of patents granted to wind turbine manufacturers that have been opposed and for which the EPO have settled the case.

* * *

* * *

Chapter 2

On the identification of process and product innovations: New insights from text mining techniques

* * *

In the framework of the Green Deal programme that seeks to re-orient research and innovation to reach climate neutrality, we study how the type of support (direct and/or indirect) for carbon-free energies can bias R&D efforts towards process or product innovations. To do so, we propose a new methodology to assess in an automatic way the product and/or process character of patents. More precisely, we use a semantic treatment of patent documents that enables us to generate a continuous measure of the relative position of an innovation between these two polar cases. This leads us to overcome several limitations of the economic literature and thus to improve our comprehensiveness of the mechanisms at work, notably how the use of these new techniques can help environmental policies to be better fine-tuned. We apply our methodology to the wind power industry and emphasize the non-neutrality of renewable support policies on the direction of innovation.

* * *

This Chapter is an adaptation of a collaboration with Marc Baudry and Béatrice Dumont.

2.1 Introduction

IN its taxonomies of innovation, the Oslo Manual (OECD, 2018, p. 70) distinguishes two major types of innovation by object, namely those innovations that change the firms' products (product innovations), and innovations that change the firm's business processes (process innovations). This distinction relies on the fact that product innovations are generally aimed at improving the characteristics of a product and/or access to a new market, whereas process innovations are aimed at improving a firm's price-cost margin (Boer and During, 2001; Rouvinen, 2002; Parisi et al., 2006). However, this categorisation is not binary. Indeed, in practice, a firm can introduce more than one type of innovation at once. A historical example is the efforts made by Charles Swan and Thomas Edison to improve the quality and duration of light bulbs by modifying the process of their production. This combination of different types of innovations is generally not tackled in the economic literature except for Fritsch and Meschede (2001) who show that on the one hand, implementation of a product innovation can make corresponding process innovation necessary. On the other hand, process innovation may enable a firm to considerably improve the quality of its products or to produce completely new products. Their results suggest that product and process innovations are often interrelated, and that these effects should be considered. When it comes to shaping public policies to impulse a technological breakthrough, the question that arises is whether these policies are likely to bias R&D efforts in favour of one type or the other, and possibly hinder the achievement of a good balance. This question is of importance for instance in the context of the Horizon 2020 Green Deal programme of the European Commission that seeks to re-orient research and innovation and drive the necessary systemic changes to reach climate neutrality and ensure an inclusive ecological and economic transition. Considering the huge financial package of the Green Deal, it seems to us the right time to disentangle the influence of these two types of innovation to better understand the factors that drive investments in green techs, and enhance productivity without harming the environment.

To illustrate our point, we look at how the type of support for carbon-free energies can drive innovation. More precisely, we study innovations related to wind power generation, as they have benefited from both direct (feed-in tariffs) and indirect (CO₂ pricing) support. To do so, we make use of recent advances in information processing techniques to improve our understanding of the innovation process. More precisely, we use a semantic treatment of patent documents which not only allows us to distinguish between product and process innovations but also enables us to generate a continuous measure of the relative position of an innovation between these two polar cases. This leads us to overcome several limitations

of the economic literature and thus to improve our comprehensiveness of the mechanisms at work, notably how the use of these new techniques can help environmental policies to be better fine-tuned.

This paper contributes to three main developments in the field of study. Firstly, we propose a methodology to assess in an automatic way the product and process character of patents and we include the possibility that a firm introduces innovations that combine two or more innovation types. We do so by using text-mining techniques. To our knowledge, this has not yet been done so far from a methodological point of view. [Cohen and Klepper \(1996a,b\)](#) use [Scherer's \(1982; 1984\)](#) classification of U.S. granted patents into product and process innovations to estimate the share of process R&D using the proportion of patents that have been classified as representing process innovations.¹ However, the aim of their paper is to study the relationship between product R&D, process R&D and firm's size. They take the classification of patents as granted. Secondly, we apply our methodology to the wind power industry and emphasize the non-neutrality of renewable support policies on the direction of innovation. Thirdly, we propose a novel measure of the “productness” of patents in order to better target renewable support policies.

This paper is organised as follows. Section [2.2](#) studies how environmental policies in favour of renewable energies can drive the R&D process of wind turbine manufacturers towards either process or product innovation; Section [2.3](#) presents the text mining methodology used to disentangle process innovations from product innovations; the results are presented in Section [2.4](#); in Section [2.5](#), conclusions and their implications are discussed.

2.2 The non-neutrality of renewables support policies on the type of innovation induced

In order to understand how environmental policies can drive the R&D of wind turbine manufacturers towards either process innovations or product innovations, we proceed in three stages. First, we briefly recall the peculiarities of the wholesale electricity market. Second, we examine how different public policies, all favouring *a priori* the production of wind power, affect the functioning of this market and the remuneration of wind power. Third, we illustrate how their differentiated impact on the remuneration of wind power drives the innovation effort of equipment manufacturers towards process or product innovations.²

¹According to [Scherer \(1982, 1984\)](#), a patent is classified as representing a process innovation if it is mainly used in its industry of origin. If it is mainly used in other industries, it is classified as a product innovation.

²For a complementary view of this aspects, see also [Hirth and Ueckerdt \(2013\)](#).

2.2.1 How does the wholesale electricity market works?

The wholesale electricity market obeys a constraint that distinguishes it from many other markets, including markets linked to energy such as, for example, that of fossil fuels. Indeed, in the absence of a mass and cost-effective storage solution (except hydraulic dams), it is a market in which it is required that the supply meet demand instantly, otherwise an outage may affect all consumers connected to the network.

Electricity demand is therefore exogenous, or in other words, it is inelastic. However, this demand is subject to intra-day cycles as well as seasonal cycles. It is also subject to hazards due to meteorological conditions or macroeconomic shocks. To cope with this, electricity production capacities must exceed almost all possible states of demand. These capacities, which correspond to different power plants, are classified in increasing order of the average variable cost of electricity production which characterizes them. This classification makes it possible to identify the capacities that are the least expensive to operate and will therefore be most often mobilized and, conversely, those which will only be mobilized rarely, in the event of unusual peaks in demand. However, in order for the capacities of a power plant to be mobilized, the selling price of the electricity produced must rise at least up to the average variable cost of production which characterizes this power plant. Figure 2.2.1 illustrates this principle. Each rectangle corresponds to a different plant. The width of the rectangle indicates the total production capacity of the plant while its height indicates the average variable cost. To meet the level of demand represented by the vertical thick line at a lower cost, all production capacities located to the left of the demand curve must be mobilized. This is the principle of merit order dispatch. The corresponding power plants produce on the condition that the price is at least equal to the average variable cost of the last plant mobilized.

It is therefore the marginal capacity, or marginal power plant, that determines the spot price on the wholesale electricity market. She receives a profit stream of just zero. On the other hand, all infra-marginal capacities receive a flow of profit per unit of electricity produced equal to the difference between the spot price and their average variable cost. This flow is represented by the double arrow in Figure 2.2.1. The plants which are the first in the merit order are therefore also those which, in expectation, receive the highest profits. They are therefore also those which can more easily incur a high amount of fixed cost linked to the investments to be made to create the corresponding generation capacity. This is why the first power plants in the merit order often correspond to very capital-intensive modes of production, such as nuclear power plants. Conversely, the profitability of power plants which are low in the merit order is ensured by their lower capital intensity. These power

plants are often, at least in Western Europe, fossil fuel-based power plants. The importance of their average variable cost stems in large part from the cost of fuel. In counterpart of this high average variable cost of operation, these power generation units can generally be quickly turned on and then turned off.

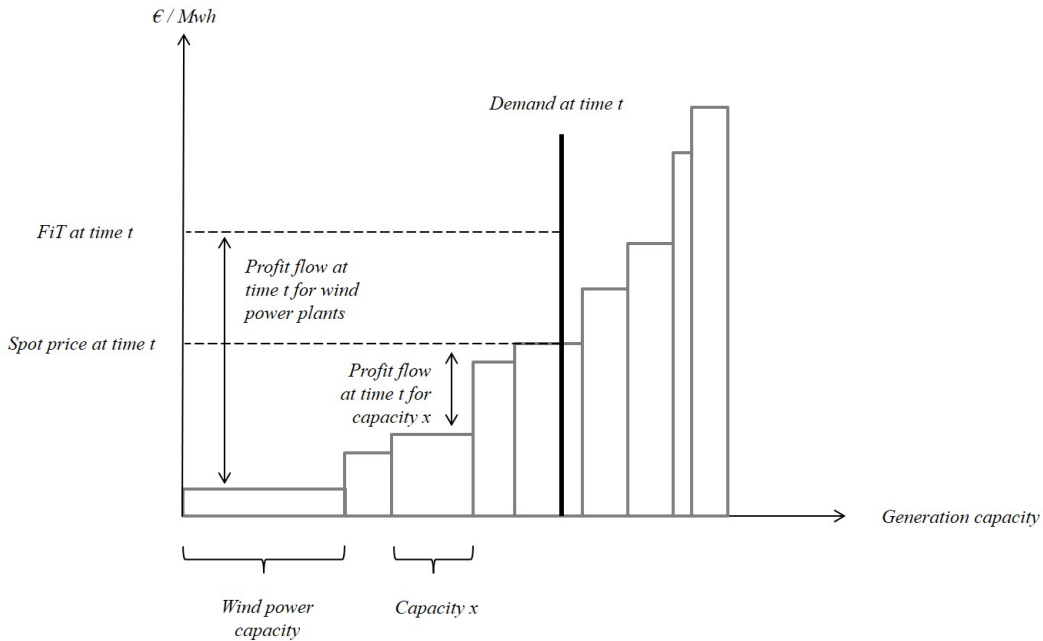


Figure 2.2.1: Wholesale electricity market under a feed-in tariff regime

2.2.2 Public policies and the return on investments on wind power generation

The peculiarity of the production of electricity from renewable sources is that it is so-called fatal energy: we do not choose when the production takes place but, when it does, it is at an almost zero variable cost. These energies, especially wind power, therefore come first in the merit order. It also means that the flow of profit is high as soon as there is production, but the expectation of profit over a year is drawn down due to the existence of periods when there is no production because natural conditions do not allow it. The initial weakness of this expectation of profit in comparison with the investment cost explains why technologies such as wind power needed the direct or indirect support of public policies in order to develop. In what follows, we focus on two policies, the feed-in tariff mechanism (direct support) and CO₂ pricing (indirect support).

A Feed-in tariff consist of a guaranteed feed-in price for electricity from wind power. In order for this guaranteed price to be decisive and to give a real boost to investment in this type of energy, it must be such that, for most possible states of demand, it exceeds the

spot price. To put it simply, we will assume in what follows that this is always the case, whatever the level of demand. As a result, the profitability of wind turbines no longer depends on market conditions but only on the meteorological hazards that govern their electricity generation. The flow of profit perceived by wind turbines when they produce corresponds to the height of the arrow in thick dotted lines in Figure 2.2.1. Note that the development of investments in wind power generation capacity shifts the merit order to the right and causes therefore a downward trend in the spot price of electricity. Under a feed-in tariff regime, wind power generation is immune to this decline, which only occurs to the detriment of the profitability of investments in all other power generation sources.

CO₂ pricing is a more indirect way to support the development of wind power generation capacities. Its impact is illustrated in Figure 2.2.2. This figure shows the new merit order resulting from the implementation CO₂ pricing for the same generation capacities than those used in Figure 2.2.1. This pricing, whether it takes the form of a tax on CO₂ emissions from power plants based on fossil fuels or the form of the additional cost induced by the establishment of an emission trading system like the EU-ETS, induces an increase in the average variable cost of production of power plants that rely on fossil fuels. This increase is represented by the new rectangles in dotted lines. The more CO₂ a power plant emits per unit of electricity produced, the more its average variable cost will increase. The increase is therefore not uniform but differentiated according to the carbon intensity of the plant. The additional average generation costs induced by the pricing of CO₂ emissions are shown in dotted lines in Figure 2.2.2. As illustrated in Figure 2.2.2, it can lead to a modification of the classification of power plants in the merit order. It is now the intersection of the demand curve with the upper limit of the dotted rectangles that determines the spot price of electricity. Figure 2.2.2 thus highlights how CO₂ pricing affects the spot price.

As wind power is carbon-free, pricing CO₂ does not affect its place in the merit order or its average variable cost of power generation. This pricing even induces an increase in the flow of profit for wind power during the production period, through the increase in the spot price that it causes. This increase, measured by the height of the double arrow in thick dotted lines, reinforces the return on investment in wind capacity. We notice incidentally that, unlike the case of the feed-in tariff, this return on investment is not insensitive with the development of all wind power capacities connected to the grid: it decreases when the merit order moves to the right due to the development of new wind farms. More important for our purposes, we note that this return on investment is not only sensitive to meteorological hazards but also, and unlike the feed-in tariff, to the state of demand. As a result, the two types of public policies will not necessarily drive the innovation of wind power suppliers in the same way.

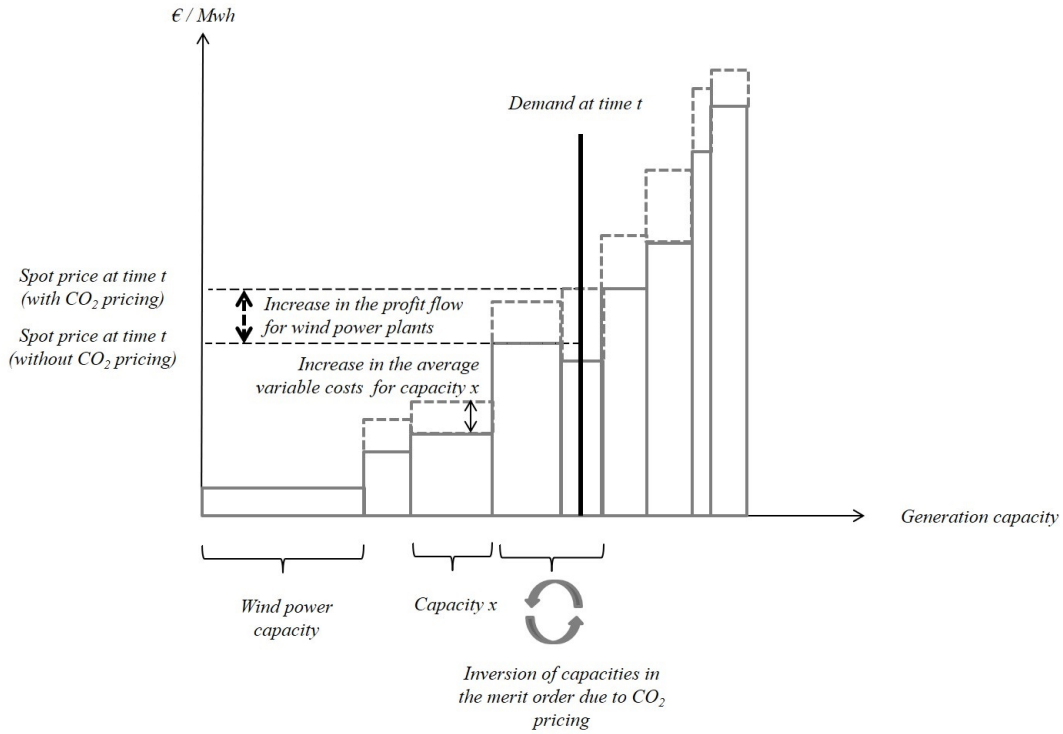


Figure 2.2.2: Wholesale electricity market under a CO₂ pricing regime

2.2.3 What type of innovation is fostered by what type of policy?

In order to illustrate how the type of support for carbon-free energies can drive innovation in wind turbines, let consider in what follows a canonical two-state of nature model. The first state of nature, referred to as E_1 , is associated with high demand for electricity but low wind speed. Conversely, the second state of nature, denoted E_2 , is associated with a low demand for electricity but a high wind speed. The states of nature are therefore such that there is a negative correlation between the level of demand for electricity and the speed of the wind. Needless to say that the stronger the wind the higher the electricity generation of a wind turbine is, at least below a certain wind speed which we assume is not crossed in state E_2 . In parallel, it is assumed that turbine manufacturers are able to invest a predetermined amount of money in R&D either to lower the production cost of wind turbines without modifying their characteristics, which corresponds to a process innovation, or to increase the production of electricity at low wind speed even if it means reducing it at high wind speed, which corresponds to a product innovation.

With a feed-in tariff, it was emphasized *supra* that the remuneration of wind farms does not depend on the state of demand. Investors will therefore seek to equip their wind farms with turbines that produce a lot, regardless of when this production takes place. They will therefore favour turbines that work well at high wind speed, but cost as little as possible.

To meet these specifications, equipment manufacturers will therefore have an incentive in devoting most of their R&D effort to process innovation. By contrast, with CO₂ pricing, investors wishing to develop new wind farms will be sensitive to when the turbines actually produce. More precisely, they are more interested in turbines capable of producing well in light winds because it is at this time that the demand and therefore the spot price of electricity is the highest. In other words, they attach importance to the fact that the production of electricity by the turbines is sufficiently in phase with the peak of demand and will therefore favour product innovation.

Of course, the choice may depend on the exact values of the different parameters, but the important point is that it is easy to find combinations of parameters that go in this direction. There will therefore be a tendency for support for wind power generation based on a feed-in tariff to promote process innovations and support based on CO₂ pricing to promote product innovations.

2.3 Methodology to disentangle patents on process innovation and patents on product innovation

In this work, we propose an attempt to identify “product patents” (i.e. patents covering product inventions). Theoretical contributions have for a long time distinguished between product and process innovation. Usually, product innovation is supposed to affect the characteristics of goods, while process innovation leads to a decrease in the production cost of the same goods. For instance, [Cohen and Klepper \(1996b\)](#) consider that both of them lead to a raise in the price-cost margin of the underlying good. In the first case, improvements in the product characteristics justifies a higher price for it; in the second case, the margin raise is reached through a decrease in the cost of production. However, instead of considering a pure dichotomy between product and process patents, we rather propose an original way to obtain a continuous measure of how much a patent is a product or a process patent.

2.3.1 Semantic treatment of patents’ text

It is an important current challenge to distinguish between product and process innovation in an “automatic” way. Patent data has been widely used for this purpose. Our approach relies on the work of [Banholzer et al. \(2019\)](#) and uses text mining techniques. These authors

consider a set of discriminatory keywords based on the idea that product innovation translates into some tangible, palpable thing. Reversely, process innovation refers to immaterial improvements. This distinction is based on laws governing the American patent system.³ Before entering into the patentability criteria, the USPTO’s Manual of Patent Examining Procedure (Chapter 2100 – Section 2106.03) defines patent eligible subject matters and mentions four of them: “*processes, machines, manufactures and compositions of matter*”. These elements can be classified in two categories. The first category includes *processes*. A process is defined as “*an invention that is claimed as an act or step, or a series of acts or steps*”. In other words, processes refer to “*actions*” in the sense that they do not consist in palpable objects by themselves. Reversely, the second category gathers the three remaining elements that are defined as “*the types of physical or tangible "things" or "products" that Congress deemed appropriate to patent*”.

Following this idea, Banholzer et al. (2019) suggest using a set of keywords displayed in Table 2.3.1. As EPO patents can also be written in French or German, they also consider French and German counterparts for those keywords. First, they proceed to a keyword search in abstracts. They emphasize that the keywords set for product patents is not exhaustive as industry actors may prefer using their field-specific jargon rather than such generic keywords to describe their inventions. Taking the example of the wind power industry, a product invention can be directly referred to as the underlying object, e.g. *a blade*, *a gearbox*. While relying on industry-specific keywords might provide useful insights, there is an over-representation of such keywords that might make their occurrence disconnected from the product/process character of the invention.⁴ Reversely, they assume that the set of process keywords better covers the process innovation possibilities. As a consequence, they consider a dichotomous classification in which a patent is considered as a process patent if she contains at least one process keyword. Reversely, she is classified as a product patent if there is no match of any process keyword, disregarding the occurrence of product keywords. Second, they proceed to a keyword search in the patent’s claims. They allow for some continuity in the “productness” measure as they are interested in the share of process claims, i.e. claims containing at least one process keyword, based on the idea that a non-process claim is a product claim by definition. By doing so, a patent can be classified as a mixed patent, i.e. belonging to both the product and process categories.

Banholzer et al. (2019) point out one main limitation of such a classification and emphasize that:

³EPO’s Guidelines for Examinations – Part F – Chapter 3.1 (EPO)

⁴For instance, the word “*Turbine*” appears on average 48.5 times per document. An example is further provided in Section 2.4

<i>Product keywords</i>	<i>Process keywords</i>
Device	
Machine	
Material	Method
Tool	Process
Apparatus	Procedure
Vehicle	Use
Compound	Utilisation/Utilization
Composition	Usage
Substance	
Article	

Table 2.3.1: Selected keywords

“One has to note that the language used in the examination guidelines differs from the language used by economists that define new products and processes in terms of their potential of serving a market or of reducing costs. The examiners’ language appears to be much more formal and technical. Just from reading patent claims, it is very difficult to determine whether product and process claims as defined by the guidelines can serve the typical functions economists have in mind when talking about product and process inventions.”

In the light of the above quote, there is indeed an important gap between economic and legalist definitions of process inventions. For instance, a manufacturing machine, while being a product, might allow for a decreased production cost. More generally, a legally defined product may be both a legally and an economically defined process. However, there is a quite clear link between the “engineer-viewed” definition of “product innovation” and the one by [Cohen and Klepper \(1996b\)](#), in the sense that the increase in the price-cost margin is the economic consequence of *technical* improvements of the underlying good. Indeed, improvements in the quality of a good is only made possible by modifying the said good. As such, product-related keywords from Table 2.3.1 better coincides with the economic definition of product innovation than in the process case.

In this paper, we extend the work of [Banholzer et al. \(2019\)](#) in two ways. First, we apply the keyword search to the full descriptions of inventions. This part of the document is dedicated to the disclosure of the invention’s characteristics. In our sample of wind power patents, the average number of words per document is 4,865 and goes up to some 125,000 words. This allows us to drastically increase the amount of information involved in the search process, in the sense that the number of keywords occurrences will most probably be higher than in

abstract or claims. This may be a solution to the issue about the use of industry-specific jargon in the sense that applicants are more likely to use generic words when going deep into the description of the invention, not least to avoid repetitions. However, there is a risk that the keywords are used to another purpose than the one of describing the invention itself and refer to the invention in an indirect way. We will discuss this in Section 2.4. Second, we propose to tackle the issue of mixed patents in a way that exploits the number of occurrences of both product and process keywords. This results to a continuous novel measure of the “productness” of patents.

2.3.2 The polar coordinates approach

For the purpose to develop our measure of how much a patent is a “product patent” or a “process patent”, we first locate each patent in a 2-dimensional space defined by the number of product and process keywords it contains. Second, we use polar coordinates to obtain a continuous measure of the “product” *versus* “process” character of a patent. The latter corresponds to the angle φ expressed in radians in Figure 2.3.1 while the radius r reflects the amount of information involved in the process.

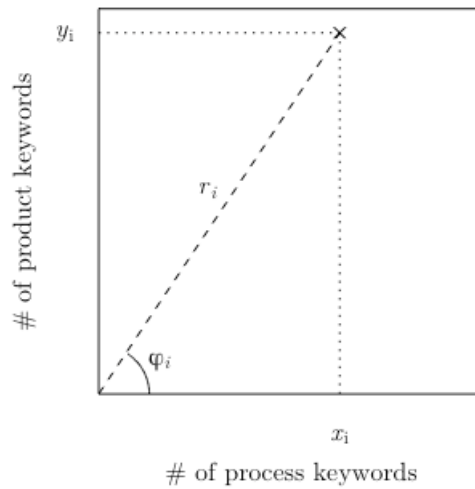


Figure 2.3.1: “Product character” of a given patent i

With $y_i \geq 0$ and $x_i \geq 0$ being, resp., the count of product and process keywords in patent document i , we have

$$\varphi_i = \begin{cases} \arctan\left(\frac{y_i}{x_i}\right) & \text{if } x_i > 0 \\ \frac{\pi}{2} & \text{if } x_i = 0 \text{ and } y_i > 0 \\ \text{undefined} & \text{if } x_i = 0 \text{ and } y_i = 0 \end{cases} \quad (2.3.1)$$

And, from the Pythagorean theorem,

$$r_i = \sqrt{x_i^2 + y_i^2}$$

For ease of interpretation, we turn the original scale of $\varphi_i \in [0, \frac{\pi}{2}]$ to $[0,1]$. To interpret the value of φ , we first distinguish between “pure” and “mixed” patents. A patent is considered as a “pure” product patent if she mentions product keywords without mentioning any process keyword. Reversely, a “pure” process patent only mentions process keywords. “Mixed” patents are patents that contain both product and process keywords. As a result, the value of φ for such patents lies in the $(0,1)$ open interval. In our setting, the value of φ_i reflects the “product character” or “productness” of patent i in the sense that the higher the number of product keywords (y_i) relative to the number of process keywords (x_i) in the document, the higher the value of φ_i and the more salient the “productness” of patent i . Also, one can define a “productness” threshold, i.e. the value of φ_i above which a patent i is considered as a “mixed product” and below which a patent is considered as a “mixed process” patent. A natural candidate for this threshold is 50% in that sense that $\varphi_i > 0.5$ if and only if $y_i > x_i$. Said in other words, a “mixed product” patent is a patent that contains more product keywords than process keywords while containing both. The reverse holds for “mixed process” patents.

r_i has a less direct interpretation, but increases with the number of keywords occurrences in patent document i . It translates the amount of information involved in the “classification” process. The fact for the computation of φ to be based on a high count of keyword occurrences reduces the uncertainty about the resulting value.

2.4 Application to wind power patents granted by the EPO

In order to illustrate the method of calculating the patent composition index between “product” and “process” elements, and highlight what it can potentially reveal about the link between public policies for the promotion of certain technologies and the orientation given to innovation, the remainder of this article is devoted to an application to EPO patent data relating to wind power. After a general presentation of the data, the results relating to the calculation of the index of the “product” *versus* “process” character of patents are detailed. The analysis focuses more particularly on the distribution of patents according to

this index and its evolution over time. The dynamics of the index distribution is linked in particular to elements of public policies supporting the development of wind energy.

2.4.1 Data

We rely on a population of 5,478 patents granted by the EPO in the wind power industry, i.e. recorded in the Y02E10/7 CPC class and sub-classes. The descriptions for those patents are collected from the EPO's [Espacenet](#) website. We applied traditional transformations to these texts: removing punctuation, accents, numbers and stopwords from the descriptions (as well as from keywords) and converting the whole text to lowercase. Then, we searched occurrences of each keyword from Table 2.3.1 in both singular and plural forms. To make sure that the related string is not part of a longer word, we checked for the presence of spaces both at the beginning and at the end of the word (e.g. " device "). To make sure any occurrence is detected, we also added spaces at the very beginning and at the end of the descriptions, so that both first and last characters of texts in the corpus are spaces. English and French languages make it easy to apply this methodology. However, the handling of German keywords was a bit more tricky due to the fact that contractions are sometimes preferred to nominal groups. For instance, *Verfahren* is a German equivalent of English word *Method* and French word *Méthode*. Also, *Rechenverfahren*, from *Rechnen* ("to calculate") and *Verfahren* ("method") is the German counterpart of *calculation method* in English and *méthode de calcul* in French. In such a context, surrounding keywords by spaces is not relevant. Thus, we only checked for the presence of the original strings in patents written in German language.

An example for this peculiarity is the [EP 1,959,132](#) patent, that relates to pitch control of turbines. None of the keywords from Table 2.3.1 appear as they are in the description of the invention, leaving the patent unclassified. However, when removing front and back spaces, one can observe 26 occurrences of the "*Pitchdrehverbindung*" product-related term. Indeed, the invention consists in a pitch control system that relies on a bearing that can be considered as a product invention.

2.4.2 Results

Using the method mentioned in the previous section, we were able to compute the value of φ for 5,399 granted patents. Only 79 patent descriptions ($\sim 1.5\%$) in our sample do not have occurrence of any of the keywords from Table 2.3.1. Proceeding the same way using patents' abstracts instead of descriptions lead to a 37% share of unclassified patents.

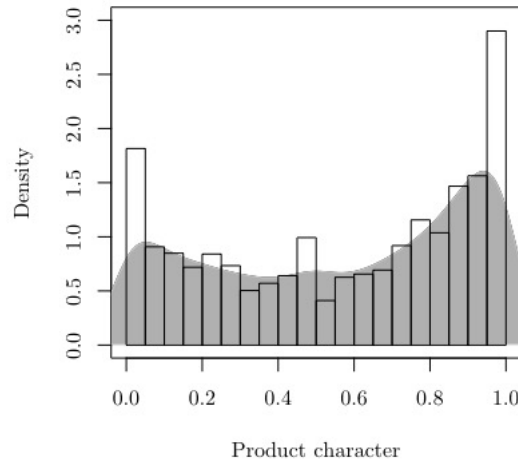


Figure 2.4.1: Distribution of φ in our sample ($N = 5,399$)

Figure 3.3.1 displays the distribution of the “product character” of (classified) patents in our sample. We first observe that the distribution is zero and one inflated: a large share of patents are almost “perfect product patents” ($\varphi \geq 0.95$) or “perfect process patents” ($\varphi \leq 0.05$), with respective shares 14.5% and 9.08%. Also, 7.17% (6.22%) of the patents are classified as “pure” product (process) patents, i.e. have a value of $\varphi = 1$ ($\varphi = 0$). However, there is a quite high number of patents belonging to both categories, which proves the usefulness of relying on a continuous measure of the “productness” of patents. Even if the distribution is U-shaped to some extent, suggesting that patents are mostly directed toward one or the other of the two polar values, patents covering products and processes in the same proportion are not so rare. For instance, nearly 13.2% of patents in our sample have a value of φ lying in the $[0.4, 0.6]$ interval. Finally, 3,085 patents in our sample are considered as product patents (both “pure” and “mixed” patents, i.e. have a value of $\varphi > 0.5$). In the same vein, 2,165 patents are classified as product patents while the 149 remaining patents have exactly the same number of process and product keyword occurrences. Regarding these classified patents, it is interesting to notice that the classification is very similar to the one using abstracts from [Banholzer et al. \(2019\)](#). Recall that they based their classification on the occurrence of process keywords: a patent is considered as a process patent if her abstract mentions at least one process keyword, as a product patent otherwise. Applying this method to our sample led us to 3,006 and 2,243 product and process patents respectively, which is very close to our results.

Figure 2.4.2 displays the relationship between the two polar coordinates φ and r . It is worthwhile noticing that product-classified patents usually involve more information. This

might be reassuring about the use of such generic keywords as those mentioned in Table 2.3.1. The latter seem to be informative despite the fact that patent holders have the possibility to use their field-specific jargon to refer to their inventions.

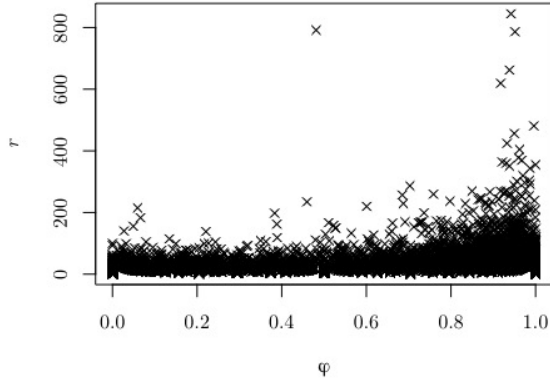


Figure 2.4.2: Relationship between φ and the amount of information involved (r)

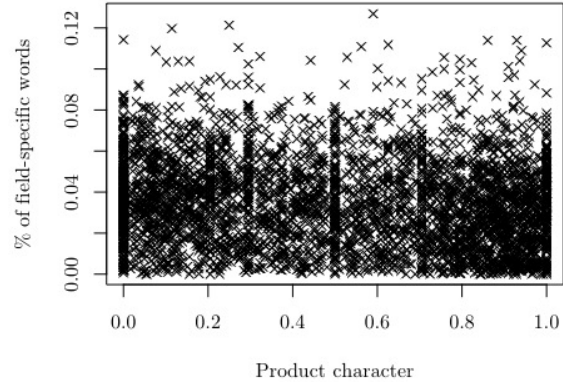


Figure 2.4.3: Relationship between φ and the share of field-specific product keywords

Regarding this latter point, we checked for the occurrences of some field-specific related keywords in all 3,875 English-written documents.⁵ We observe from Figure 2.4.3 that they are likely to appear whatever the value of φ . Thus, such words may be too generic to allow for a clearcut distinction between product and process inventions and are likely to be employed in another purpose than the one of describing the product itself.

In addition, the value of φ appears to be sensitive to the language in which the patent is written. Whereas French-written patents account for a very small share of in our sample, almost 27% of patents are written in German. Yet, we observe that a large share of German-written patents are classified as product patents. For instance, more than 50% of them have a productness value above 0.82 (see the top part of Table 2.4.1). By contrast, only about 25% of English-written patents reach such a value. A first explanation of this result is that, quite early in our period of interest, German language was used to a higher extent than English. Figure 2.4.4 illustrates this by showing the share of patents written in French and German over time. At that time (i.e. before year 2005 at which the share of patents written in another language than English stabilises around 25%), as will be shown *infra*, innovation was mainly product-oriented. Thus, the high representation of German-written patents in early time may be part of the rationale. However, the bottom part of Table 2.4.1 shows that it is not a sufficient explanation. Indeed, whereas the quartile values are lower for patents filed after year 2005, we still observe higher statistics for patents written in

⁵The set of keywords includes *turbine*, *rotor*, *blade*, *nacelle*, *tower*, *generator*, *gearbox* and *bearing*, which are among the main components of any wind turbine.

French and German patents. For instance, the average value of φ for German-written patents filed after 2004 is almost 0.7. The same statistic for English-written patents is a bit more than 0.5. A second explanation for this is that most of the top wind turbine manufacturers are German companies. It is possible that these manufacturers are driving product innovation in the field, while other non-specialist firms are more active on the process side. A third possible explanation is related to keywords. Recall that German language relies on contractions of words. In our methodology (see sub-section 2.4.1), we took into account contractions of the German counterparts of keywords from Table 2.3.1 with prefixes and suffixes. Thus, the set of keywords is multiplied and may cover a wider technological reality. This would fall in line with the fact pointed out by Banholzer et al. (2019) that generic keywords from Table 2.3.1 are not sufficient to accurately capture the product character of patents. However, French-written patents tend to be product-oriented in an even extended way despite the use of the Table 2.3.1 restricted set of keywords in the computation of φ . It will be interesting to explore this phenomenon in further research.

Language	Period	Min.	1st Qu.	Median	Mean	3rd Qu.	Max.	N	Unclassified
English	All	0	0.1948	0.5000	0.5074	0.8263	1	3,875	49
German	All	0	0.5155	0.8286	0.7060	0.9567	1	1,473	28
French	All	0	0.5565	0.8647	0.7044	0.9595	1	130	2
English	Before 2005	0	0.2422	0.5456	0.5367	0.8498	1	278	0
	2005 and after	0	0.1915	0.5000	0.5055	0.8231	1	3,577	49
German	Before 2005	0	0.6257	0.8656	0.7465	0.9750	1	313	16
	2005 and after	0	0.5000	0.8228	0.6958	0.9489	1	1,155	12
French	Before 2005	0.0353	0.7716	0.8743	0.7744	0.9849	1	23	2
	2005 and after	0	0.5132	0.8512	0.6878	0.9560	1	106	0

Table 2.4.1: Summary statistics for φ , by language

The violin plots in Figure 2.4.5 displays the evolution of the distribution of φ across time from 1990 to 2017. One can appreciate the changing in the shape of the distribution. At the beginning of the period, the plots are similar to funnels, suggesting that innovation in the field mostly focused on product innovation. From the 2004-2005 period, there is a significant modification in this distribution (evidenced by the Kolmogorov-Smirnov test in Table 2.4.2) and process innovation becomes more prominent. At the next period (2006-2007) there is more “pure process patents” ($\varphi = 0$) than “pure product patents” ($\varphi = 1$). This is evidenced by the value of the mode (red point on the figure). White points and the dashed line display the values and evolution in the median of the distribution while black points and the solid line provide the same information with regard to the mean of the distribution. We also observe a clear decrease in these values until year 2004. Nonetheless, both the median and the mean remains above the 50% threshold over the whole period.

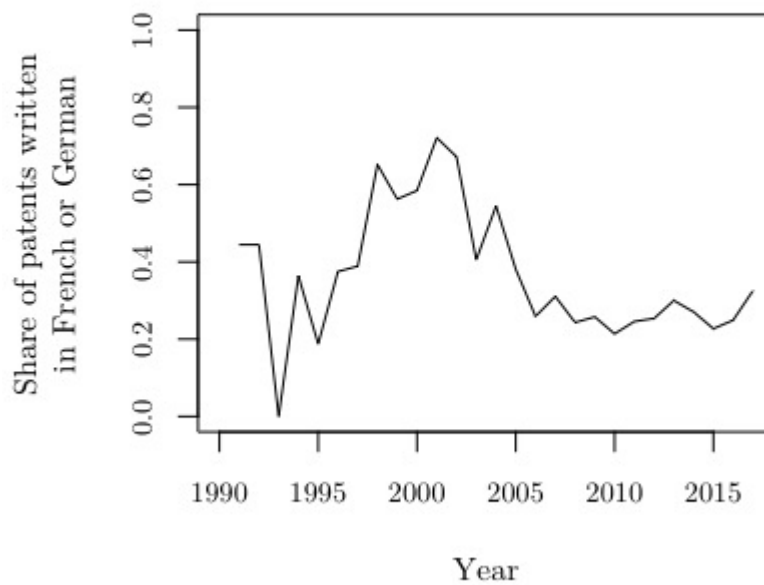


Figure 2.4.4: Evolution in the share of French or German written patents

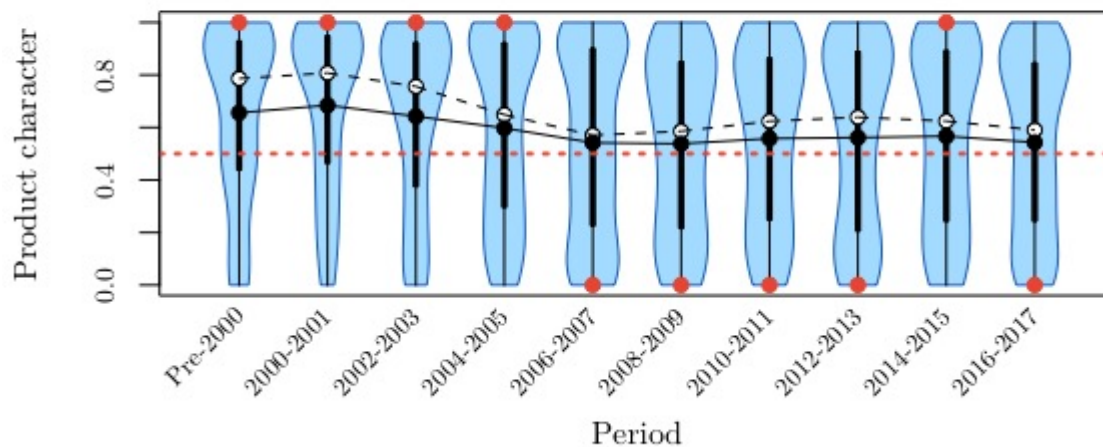
Figure 2.4.5: Chronological evolution in the distribution of φ

Figure 2.4.6 shows the evolution in the number of product and process patent applications. Here, we set the “productness” threshold to be 50% (see Section 2.3). This amounts to consider as product (process) patents those mentioning more product (process) keywords than process (product) keywords. One can observe that product and process innovation

	Pre- 2000	2000- 2001	2002- 2003	2004- 2005	2006- 2007	2008- 2009	2010- 2011	2012- 2013	2014- 2015	2016- 2017
D	-	0.104	0.115	0.145*	0.078	0.059	0.036	0.055	0.039	0.077

*Note: * indicates significance at the 5% level.*

Table 2.4.2: Kolmogorov-Smirnov two-sided test

follow a quite similar pattern, but with a time lag. Indeed, the cumulative number of patents significantly increases at the end of the 1990s while the raise in the number of process patents applications starts at the beginning of the 2000s. However, the divergence in the curves that initiates at the end of the 2000s reflects the fact that the number of product patents grows faster than the one of process patents. This conclusion is mitigated when excluding mixed patents and focusing on pure patents, i.e. patents with extreme values of φ (0 or 1). From Figure 2.4.7, we observe that, indeed, the increase in the number of product patent applications precedes the one in the number of process patents. However, we do not observe a divergence in the curves' trajectory and rather observe a similar – still lagged – evolution between “pure product” and “pure process” innovation.

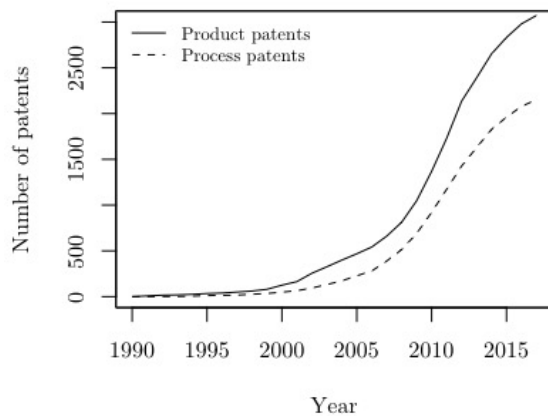


Figure 2.4.6: Evolution in the number of product ($\varphi > 0.5$) and process ($\varphi < 0.5$) patents

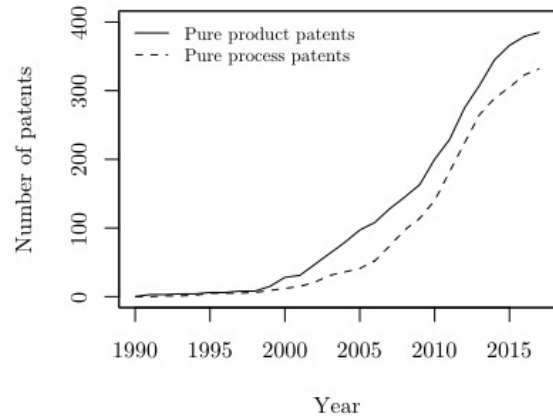


Figure 2.4.7: Evolution in the number of pure product ($\varphi = 1$) and pure process ($\varphi = 0$) patents

2.4.3 Exploring the link with public policies

In any case, it appears that the mid-2000s marked a breakthrough in the orientation of the patents granted. A first explanation of this rupture could be the change in the development

of wind energy. This change is illustrated by Figure 2.4.8 showing the evolution of the cumulative installed capacities at the global level (from 1996 to 2019) and in all the European Patent Convention member countries (from 2004 to 2019), which are therefore potentially covered by a patent granted by the EPO.⁶ It appears that in 2004, and probably for all previous years as well, most of the capacities were installed in countries of the EPO area. However, from 2004, cumulative worldwide capacities increased significantly more rapidly than the cumulative total capacities in the EPO area. In other words, from 2004, countries outside Europe have acquired growing importance in wind energy. This break could explain a change in the direction of innovation in wind turbines, which has become more sensitive to the extra-European context. However, this does not explain why, over the very last years of the study, the effect seems to diminish, or even reverse and return to a configuration close to the first years of the study if one relies on Figure 2.4.5.

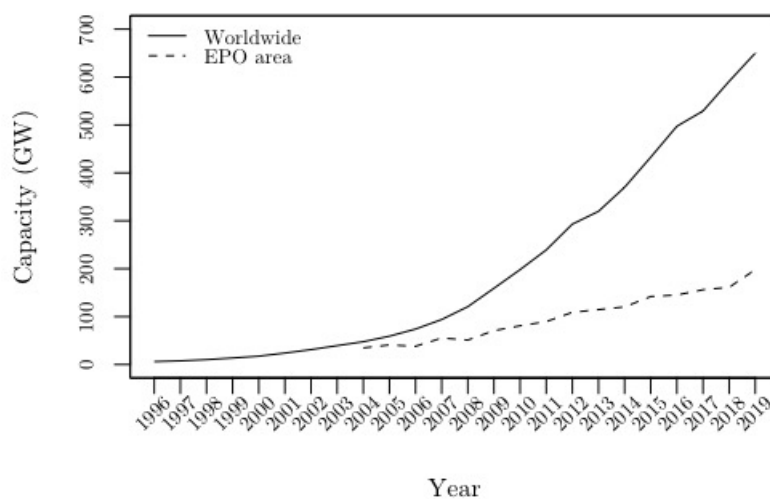


Figure 2.4.8: Cumulative wind power installed capacities within the EPO area and worldwide

Data source: Global Wind Energy Council and European Wind Energy Association

The dynamics of public policies to support the development of wind power within Europe is probably a better candidate to explain the breakthrough in the orientation of EPO patents in the mid-2000. Figure 2.4.9 attempts to highlight it on the basis of two indicators.

The first indicator seeks to reflect the support for wind energy provided by feed-in tariffs in Europe. It is constructed from data established by the OECD relating, on the one hand, to the average amount of feed-in tariffs applied by OECD member countries, as well as certain non-OECD countries and, on the other hand, the length of time during which

⁶Data come from the Global Wind Energy Council and from the European Wind Energy Association.

wind farms can benefit from this support.⁷ As a small amount of FIT can be compensated by a long duration, and vice versa, the two measures have to be combined into one. For this purpose, we calculated the discounted sum over the duration of the support of the amount of feed-in tariff received for a production of 1 MWh per year (the discount rate was set at 2%). First, this income from feed-in tariffs, expressed in constant 2015 euros, was calculated for each country covered by the EPO. Secondly, a weighted average over all of these countries was calculated. The weights used correspond to the share of the cumulative installed capacities of each country in the total of countries covered by the EPO. The selected indicator thus takes into account the relative importance of each country in the European wind turbine market. More precisely, this weighting system implies that, if a country with large installed capacities does not adopt a feed-in tariff mechanism to support wind power, then the average indicator tends to be low. The average indicator is therefore sensitive to the number of countries with a FIT mechanism and to the capacity installed in these countries compared to countries without FIT. The second indicator used in Figure 2.4.9 is the price of CO₂ on the EU-ETS.⁸ The carbon market was put in place from 2005 and the price per tonne of carbon stood at around 20 euros per tonne of CO₂ for several years. But from 2008, under the effect of the subprime crisis, the price fell and even drop to around 5 euros per tonne from 2013 to 2017 and then rose again. By contrast, the average level of FITs revenue remained fairly stable until 2015 despite some annual variations. It was not until 2015 that, faced with the cost of this support for the public authorities as well as the maturity acquired by this source of energy (in particular the fact that electricity from wind became closer to grid parity), most countries have gradually reduced this support, or even abandoned it. It follows from these trends underlined by Figure 2.4.9 that, despite the establishment of the EU-ETS from 2005, the support for wind energy provided by the FITs has been more constant and significant than the support provided by the carbon market. Taking into account the theoretical analysis of the impact of these two types of policies carried out in Section 2.2, it is therefore quite consistent to observe that this rather pushed up the “process” component of innovations compared to their “product” component, even if the latter has remained globally dominant. The fact that over the last two years (2020 and 2021), not covered by the study, the price of CO₂ has risen sharply to around 60 euros per tonne while FITs are becoming less and less popular insofar as the wind power has almost reached grid parity, and should ultimately lead to a reversal of this trend.

⁷See the [OECD Statistics documentation](#).

⁸Data have been collected from the European Energy Exchange (EEX) website.

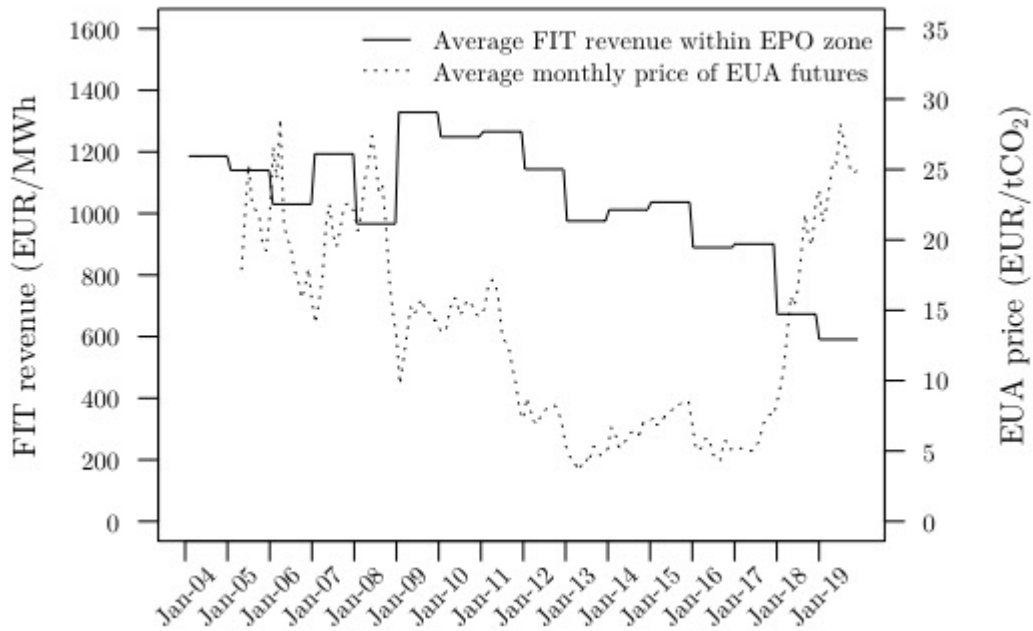


Figure 2.4.9: Comparison of FIT support and CO₂ pricing support
Data source: OECD and EEX

2.5 Conclusion

In this paper, focusing on the wind power industry in Europe, we first emphasized that renewables support policies have a non-neutral effect on the direction of innovation and took the example of the feed-in tariffs system and the one of CO₂ pricing. The idea is that the remuneration of wind parks in the presence of a CO₂ pricing system is correlated with electricity demand. As a consequence, wind industry actors will have an incentive to produce more when demand (and thus spot price) is higher. If this moment coincides with low wind speeds, it is of interest to improve their turbines so that they better respond to demand in this context. Reversely, the remuneration of a farm under feed-in tariff regime is decorrelated with electricity demand. Thus, wind industry actors will be more likely to direct their R&D effort towards process innovation as they do not care when production happens. If turbines are efficient at high wind speeds, increasing profit is made possible by decreasing the cost of the technology.

We then proposed a methodology to assess the product and process character of patents. Based on a legal definition of product and process inventions, we applied the keyword search suggested by [Banholzer et al. \(2019\)](#) to patents' descriptions. Then, we proposed a novel measure of the "productness" of patents which value depends on the frequency of occurrence of these keywords. The detailed analysis of the distribution of this measure through time

highlights an interesting dynamics that can be in part correlated with public policies in favour of the development of wind power.

* * *

Chapter 3

Do patent holders push the technology frontier forward? Evidence from the wind power industry

* * *

In this chapter, we rely on technical characteristics of turbines to construct the technology frontier of the wind power industry. Then, we compute contributions of firms to pushing the frontier forward on the basis the location of their turbine, entering the market at a given year t , relative to the $t - 1$ frontier. Especially, one turbine – and the associated manufacturer – is considered as innovative if it lies above the technology frontier. Confronting this objective measure of technical change with patent portfolios at the firm level leads us to conclude that (i) at the beginning of the period, technical change happened despite weak patenting activity, (ii) firms having contribution to technical change are mostly those holding patents, and (iii) there is a positive relationship between patent counts and the extent of these contributions. If these results are positive with regards to the use of patents as a proxy of technical change, we emphasize the need to account for renewals and the time-to-market of innovations.

* * *

3.1 Introduction

BACK to the year 1474 in Italy, the promulgation of the *Parte Veneziana* has paved the way to our current patent systems. The economic justification of this hardly new system is to provide potential inventors an incentive to invest in research and development. Knowledge has the characteristics of a public good: it non-excludable as well as intrinsically non-rivalrous. The main issue about knowledge comes from the fact that it is costly to produce, as is apparent from the huge amounts of R&D spending from both the public and private sectors. The consequence of the latter is the so-called *problem of appropriability*: agents lack incentive to invest in research due to the fact that competitors are able to reproduce the invention at (almost) no cost. In the classical microeconomic framework, the production of the invention by competitors tends to lower the price toward its marginal cost of production in such a way that the original inventor can not cover its research cost. The patent system is supposed to be a solution to this problem. By providing a right to exclude anyone from the reproduction of an invention, the system turns the patented knowledge into a club good. Reproducing the patented invention requires the consent of its inventor and usually the payment of royalties. Still, such a system may have socially harmful consequences as the right to exclude is similar to a monopoly power. The pioneering work of Nordhaus (1969a), who is the first to provide a formalization of the economics of the patent system, illustrates the trade-off that is faced by the regulator and the necessity of providing a sufficient incentive (i.e. reward) to inventors while constraining the associated welfare losses. The research of the optimal patent length (i.e. lifetime) and breadth (i.e. scope of protection) has lead to an abundant subsequent literature (see, e.g., Tandon, 1982; Klemperer, 1990; Gallini, 1992; Denicolo, 1996). In practise, patents' maximal lifetime is 20 years in most of modern patent systems.¹ If patent breadth is more abstract, it relates to which specific elements will be actually subject to patent protection. Also, the patentability criteria and their appreciation by patent office examiners play a key role in defining the degree of novelty and inventive step (non-obviousness in the U.S.) that is required for an invention to be patented.

As such, the patent system is a second-best solution to the appropriability problem. In an early study, Machlup (1958) already emphasized that:

¹This is a maximum value as maintaining patent protection usually requires the payment of an annual (or, at least, regular) fee. Moreover, in some sectors, patent length can be extended. For instance in Europe, pharmaceuticals may be subject to the *Supplementary protection certificate*, which has a 5 years lifetime in addition to the common 20 years. It is *inter alia* supposed to compensate the duration of premarket approvals.

“If we did not have a patent system, it would be irresponsible, on the basis of our present knowledge of its economic consequences, to recommend instituting one. But since we have had a patent system for a long time, it would be irresponsible, on the basis of our present knowledge, to recommend abolishing it.”

More recently, this issue has experienced a renewed interest (see e.g. *The Case Against Patents* by [Boldrin and Levine, 2013](#)). This literature argues that the patent system tends to retard innovation instead of spurring it. Two main rationales for this are (i) the fact not all inventions are patented, and (ii) that patents may be filed for legal or rent-seeking purposes. The even more recent publication of *The Case for Patents* by [Spulber \(2021\)](#) reveals the cleaving character of the patent system.

It is thus still worthwhile to evaluate the actual impact of patents on innovation. It raises the issue of the measurement of innovation. Patent counts themselves are probably the more widely used proxy for the innovative activity of firms or countries. Indeed, beyond the public policy instrument, the patent system has the advantage of data. Patent offices scrupulously record patent applications as well as a whole lot of information about their content. But relying on patent data as a measure of innovative performance precisely implies a correlation between patent and technical change. If the patent system fails to promote innovation, patent data is at best an imperfect measure of innovation.

One large strand of literature have focused on tackling the issue of heterogeneity in patents “value” or “quality”. In addition to be widely and easily available, patent data provide a large number of quantifiable characteristics that are often referred to as patent “metrics”. The latter are usually considered to reflect patent “quality” or “value” (see [Squicciarini et al., 2013](#), for a summary of the most widely used metrics for this purpose). Correcting for the quality of patents allows one to take into account the heterogeneity of patented inventions. Indeed, a single patent can protect a breakthrough invention as well as a very incremental improvement of an existing invention. Relying on such metrics is based on evidence about the link between these particular metrics and the “value” of a patent. For instance, [Harhoff et al. \(2003\)](#) use survey data on the valuation of patents by their holders. The concept of patent “value” has to be disentangled. The literature in this field distinguishes between patents social value and private value. For instance, for the former, [Trajtenberg \(1990\)](#) finds that patent counts weighted by forward (i.e. received) citations are closely related to a measure of social welfare of innovations (earlier developed in [Trajtenberg, 1989](#)). For the latter, research has mainly focused on firm’s stock market value (see, among others, [Pakes, 1985](#); [Hall et al., 2005](#)).

Some arguments of people that are against the patent system reflect the fact that private and social value might be disconnected. For instance, a blocking patent (i.e. filed in the purpose of blocking access to a given technology) may consist of a very small step-up. But if this particular patent allows its holder to maintain a market position, by e.g. preventing competitors to invent around a key technology, it might be highly valuable to the firm. What seems interesting in the context of assessing the role of patents in the technical change process is to focus on objective (i.e. patent-independent) measures of technical change in its “social” aspect. The work of [Trajtenberg \(1990\)](#) is especially relevant in this regard. The author is interested in Computed Tomography scanners and bases his measure of product innovation on the difference in social welfare between two periods. Each period is characterized by different choice sets of products which can experience improvements in quality, with regard to some observable and quantifiable characteristics of goods. He concludes that citations-weighted patent count is correlated with the welfare variation, while simple patent count is not. [Boldrin et al. \(2011\)](#) use labour and total factor productivity as a measure of innovation at the industry level in the U.S. They show no correlation with patent citations, leading them to conclude that “*the larger fraction of productivity-enhancing innovations are not captured by patents*”. On the opposite, [Baudry and Dumont \(2017\)](#) highlight a positive correlation between patent counts and total factor productivity in seven countries (China, France, Germany, Japan, Korea, Sweden, U.S.). [Sampat and Ziedonis \(2004\)](#) proxy the “economic” value of patents by (i) the fact for a patent to be licensed and, if so, (ii) the revenue from licensing. Their results show that patent citations are good indicators of whether a patent is licensed, but not of subsequent revenue. Also based on licensing revenues, [Abrams et al. \(2013\)](#) evidence an inverted-U relationship between the value of patents and the number of citations they receive. They argue this is due to the fact that valuable patents are more likely subject to strategic patenting which, by deterring market entry, causes fewer citations. In a more historical perspective, [Lampe and Moser \(2010\)](#) wish to examine how did the 1856 U.S. sewing machine patent pool impact innovation in this field. In the same vein as in the present paper, they use, along with patent data, data on machine’s stitches per minutes as an independent measure of innovation.

In this paper, we propose an original patent-independent measure of innovation at the firm level in the wind power sector. This measure is based on technical characteristics of turbines. For this purpose, the wind power industry is interesting in many ways. First, wind power technology is quite simple technology in the sense that improvements in the technology may be proxied by a number of numeric characteristics. The latter will be used to construct the technology frontier each year between 2000 and 2017 and compute contribution of new models to the past-year frontier. Second, the number of patent applications and grants

in the field have experienced a huge increase since the mid-2000. At the same time, the European wind turbine market tends to get more concentrated, with 6 top players sharing nearly 95% of market shares at the end of the period. Within this context, one can wonder whether patents held by firms have had an actual impact on innovation or have been filed for anti-competitive purposes. Third, wind power technology is considered as a very promising solution to decarbonise the worldwide energy sector. As such, the wind power technology has been subject to massive public support from most European governments. Maybe the most remarkable policy has been the implementation of feed-in tariffs to create a stable and ongoing demand for low-carbon technologies. It is also interesting to notice that patent policies have been adjusted for these technologies. In some countries, “green” technologies have been eligible to the so-called *fast-track applications*, which allows inventors to request for an accelerated examination of their patent applications (see [Dechezleprêtre, 2013](#), for an overview and an evaluation of fast-track applications). Finally, innovation studies of the wind power sector extensively rely on patent data to assess different aspects of the innovative process: knowledge spillovers ([Braun et al., 2010](#); [Grafström, 2018](#)), learning-by-searching ([Tang and Popp, 2016](#); [Grafström and Lindman, 2017](#); [Odam and de Vries, 2020](#)), technology transfers ([Haščič and Johnstone, 2011](#)), policy studies ([Johnstone et al., 2010](#); [Lindman and Söderholm, 2016](#); [Schleich et al., 2017](#); [Zhang et al., 2018](#); [Lin and Chen, 2019](#)), technological trajectories ([Huenteler et al., 2016](#)), technology development and market maturity ([Dubarić et al., 2011](#); [Baudry and Dumont, 2016](#)), efficiency of R&D ([Kapoor et al., 2012](#)).

The paper is organized as follows. Section 3.2 proposes a method to assess the contributions of wind turbine manufacturers to technical change in their field. Sub-section 3.2.1 is dedicated to some physics of wind power and the related characteristics of wind turbines. Sub-section 3.2.2 discusses the DEA method and our adaptation of it to the issue of measuring contributions of firms to technical change. Sub-section 3.2.3 provides some descriptive statistics about technical progress in the wind turbine industry between 2000 and 2017. Section 3.3 dives into the actual patent – technical change relationship. Sub-section 3.3.1 displays different measures of the so-called *knowledge stock* of firms based on patent data. Sub-section 3.3.2 details the econometric specification and discusses the results. Section 3.4 concludes.

3.2 The measurement of firm-level contributions to technical change

In this section, we rely on technical data of turbines provided by THEWINDPOWER database to construct an indicator of firms' contribution to technical change.

3.2.1 Some basic wind energy physics

This paper focuses on a specific aspect of innovation, namely the increase in power output.² THEWINDPOWER provides for hundreds of wind turbine models some basic characteristics, such as rated power, hub height, rotor diameter or cut-in, cut-off and rated wind speeds. But it also provides the power curves of wind turbines, i.e. the curve that associates a power production to different wind speeds (with 0.5 m.s⁻¹ bins). The power curve of a turbine is defined by the following equation:

$$P(V) = \underbrace{\frac{1}{2} \times \rho \times \pi \times \left(\frac{D}{2}\right)^2}_{P_w(V)} \times V^3 \times C_p(V) \quad (3.2.1)$$

where V is the wind speed (in m.s⁻¹), $P(V)$ the power output associated with wind speed V (in W), D the rotor diameter (in m), ρ the density of air (in kg.m⁻³), $C_p(V)$ the power coefficient associated with wind speed V and $P_w(V)$ the amount of wind energy captured by the rotor at wind speed V (in W).

From Equation 3.2.1, we first observe that the power output of a turbine is simply the kinetic power of the wind captured by the rotor times the power coefficient. The latter then reflects the ability of a turbine to convert kinetic energy into electric energy. Second, one can notice that the amount of wind captured by the turbine depends on its rotor size: the larger the swept area (i.e. the blade length), the higher the amount of energy entering the generator, and the higher the electric output, *ceteris paribus*. Other variables in Equation 3.2.1 include the wind speed and the air density.

By considering that the two latter variables are independent from the characteristics of a turbine, there remains two levers that wind turbine manufacturers can act on to increase the power output of their machines. First, it is possible for them to raise the rotor diameter of turbines in order to increase the wind energy input that will be captured by the machine.

²Thus, we focus on *product innovation* due to the lack of cost data. However, some important aspects of wind turbine's product innovation, such as noise reduction or wildlife protection, are neglected due to their unquantifiable character.

Second, they can improve the efficiency of conversion of kinetic energy into electric energy, i.e. increase the power coefficient $C_p(V)$ of the turbine.

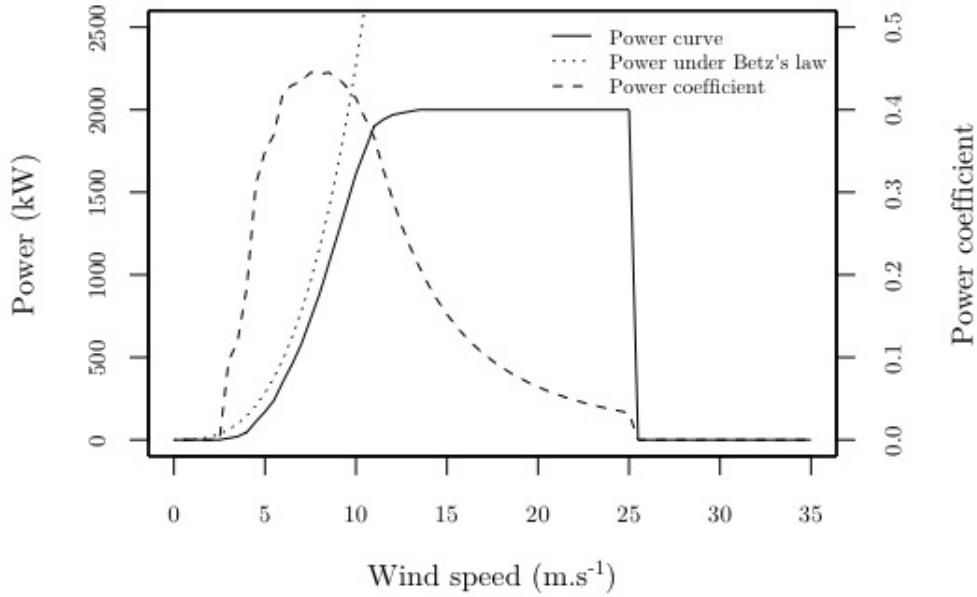


Figure 3.2.1: Power curve, power coefficient and the Betz's law

Both the power output and the power coefficient are measured and calculated at a given wind speed. The power curve displayed on Figure 3.2.1 is a typical modern turbine power curve. Once a certain wind speed is reached, namely the *cut-in wind speed*, the turbine starts to produce. This usually happens at wind speeds between 2.5 and 4 m.s⁻¹. From this point, the turbine output increases until it reaches its nominal (i.e. maximal) power. This happens at the so-called *rated wind speed* which is usually around 12 m.s⁻¹. Since then, the turbine operates at the constant rated power until the *cut-off wind speed* is reached. At this point, usually to be 25 m.s⁻¹, the turbine is stopped for safety considerations.

Still from Equation 3.2.1, one can observe that the wind input is related to the cube of the wind speed. As such, keeping the power output constant at high wind speeds negatively affects the power coefficient. The latter is displayed as the dashed curve of Figure 3.2.1. We observe that the power coefficient reaches its maximal value on the ascending part of the power curve due to the fact that the amount of kinetic energy raises faster than the associated electric output. The power coefficient is subject to the Betz's law, that states that the theoretical maximum of the power coefficient is $\frac{16}{27} \approx 59.3\%$. The dotted curve of Figure 3.2.1 displays the power output of a fully efficient wind turbine (i.e. maintaining its

power coefficient to its maximum value along all wind speeds). In practise, the maximum value of the power coefficient is 45% due to aerodynamic, mechanical and electrical losses.³ Further in the paper, we will assess the contribution of new wind turbine models using those two characteristics: the size of the turbine and its performance, based on the power coefficient. However, we wish to compute a unique (i.e. that takes into account the continuum of possible values of V) measure of the ability of turbines to convert the energy of wind into electric energy. To do so, we rely on the Annual Energy Production (AEP), or at least its expected value. The THEWINDPOWER database provides information about the wind class of wind turbines, i.e. the optimal conditions in which they are designed to operate. The International Electrotechnical Commission (IEC) proposes a classification of wind sites into high, medium and low wind sites. Each of these classes is characterised by a mean wind speed; this is summarized by Table 3.2.1.

Wind class	Average wind speed at hub height (m.s ⁻¹)
IEC I	10
IEC II	8.5
IEC III	7.5

Table 3.2.1: IEC wind classes and associated average wind speeds

Based on this value and relying on common meteorology techniques, one can approximate a wind speed distribution associated to each IEC class. Thus, knowing the IEC class of a turbine and its power curve allows us to compute the expected value of the Annual Energy Production. The latter is given by:

$$AEP = T. \int_{V_{ci}}^{V_{co}} [(f(V) \times P(V))] dV \quad (3.2.2)$$

where $T = 8,760$ is the number of hours per year, $f(V)$ the probability of facing wind speed V , $P(V)$ the wind turbine power curve (in W) and V_{ci} and V_{co} are resp. cut-in and cut-off wind speeds.

Focusing on the two first levers, we observe from Eq. 3.2.1 that the power coefficient is expressed for each possible value of V . One wishes to have a unique measure of the ability of turbines to convert the energy of wind into electric energy. To do so, we rely on the Annual Energy Production (AEP).

³In this study, we will focus on the production of a single wind turbine. Thus, we neglect wake losses that are due to a modification of the wind structure by turbines standing nearby.

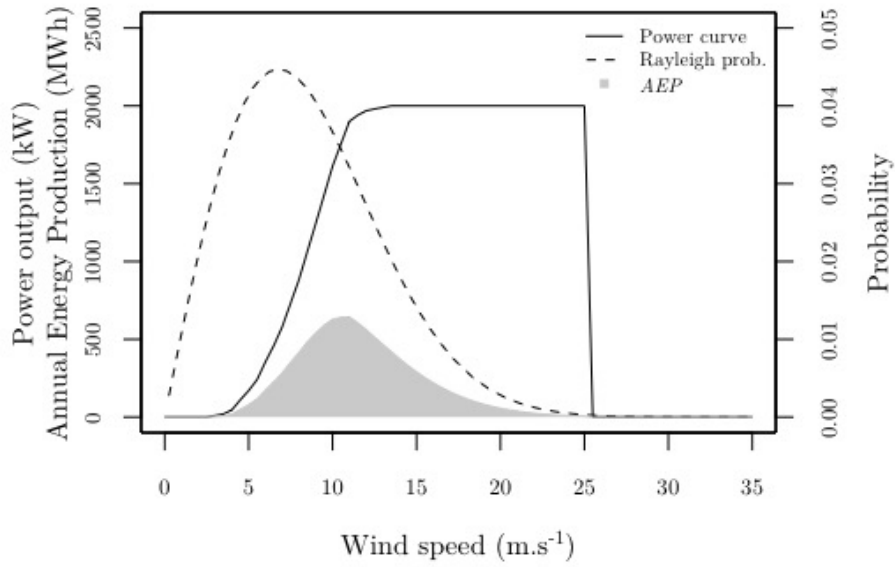


Figure 3.2.2: AEP computation for the Vestas V90/2000 IEC II wind turbine model

Computing the *AEP* of turbines has the advantage of taking into account the whole shape of the power curve. As observed from Figure 3.2.2, wind is more likely to blow around at $7\text{--}8\text{ m.s}^{-1}$ while turbine’s rated power is usually reached for wind speeds around 12 m.s^{-1} . As such, the ascending part of the curve is as important as the maximum value of it, what makes the *AEP* value preferred to the turbine’s rated power.

Moreover, we can now compute r the “global” power coefficient for a given turbine, i.e. computed along the continuum of possible values of V .⁴ It is given by:

$$AEP = D \times r \quad (3.2.3)$$

Finally, we have a unique index that translates the ability of turbines to efficiently convert kinetic energy into electric power, being given the amount of wind input (i.e. the rotor size). In the next subsection, we will refer to it as the performance level and turbines will be defined by their size – performance combination (in the same vein as Jamieson, 2018).

⁴Jamieson (2018) calls it the “electricity production efficiency” while Masters (2013) refers to it as the “productivity” of a turbine.

3.2.2 Technology frontier and contributions to technical change

In this paper, we consider that the size – performance combination is the output from the innovation process and, especially, we will consider no specific input in this process. Indeed, the subject matter of the paper is not to assess the efficiency of the innovation process, but to compare several models of turbines with regard to the characteristics mentioned above. Especially, we wish to assess the contributions of each model to the state of art. Our approach in this objective is based on Data Envelopment Analysis (DEA) that originates in the work of [Charnes et al. \(1978\)](#) and has been significantly extended by [Banker et al. \(1984\)](#). Based on the technical characteristics presented in the previous section, the idea is that the *technology frontier* evolves over time as technical change (i.e. evolution in the size–performance combination, see Equation 3.2.3) happens.

Technical innovation leads to the commercialization of new turbines by their manufacturers. One can locate any turbine in a two-dimensional space of characteristics: size and performance, the product of them being the annual electric output. On the first hand, rotor size can be raised for a turbine to capture more kinetic energy from the wind. On the other hand, WT manufacturers can improve more downstream elements, such as the generator or components, to better convert the captured energy into electricity. In both cases, holding the second output constant leads to an increase in the electric production of the turbine.

There are several assumptions underlying the DEA method. First, we implicitly assume that increasing the value of one output without sacrificing the other output is challenging. In other words, there is a certain degree of substitution in the *frontier of possible characteristics*. As we will observe further, data from the THEWINDPOWER database tend to validate this assumption. Second, it is considered that hypothetical combinations lying on the frontier are linear interpolations of existing efficient turbines. This can be relaxed by using the Free Disposal Hull (FDH) method.

In this paper, we will construct several measures of contribution to technical change. In all cases, a model will be compared to a benchmark point located on the frontier.

Contribution measure based on radial distances

In the original one input, two outputs DEA model, the efficiency measures are computed based on productivity levels (i.e. output/input) and their radial distance. Since we have no input in our setting, the interpretation is direct: the productivity level confounds with the absolute output level. The traditional efficiency measure for non-efficient models translates the potential for increasing simultaneously the “production” of outputs. Thus, by definition, models that are considered as efficient have an efficiency of one. In fact, what we are

interested in is the intake of a single, new wind turbine. Let's consider three models, denoted A, B and C, that enter the WT market at period t . To assess the contribution of one particular model to technical change, we use the technology frontier at period $t - 1$ as a benchmark. Figure 3.2.3 provides an hypothetical example.

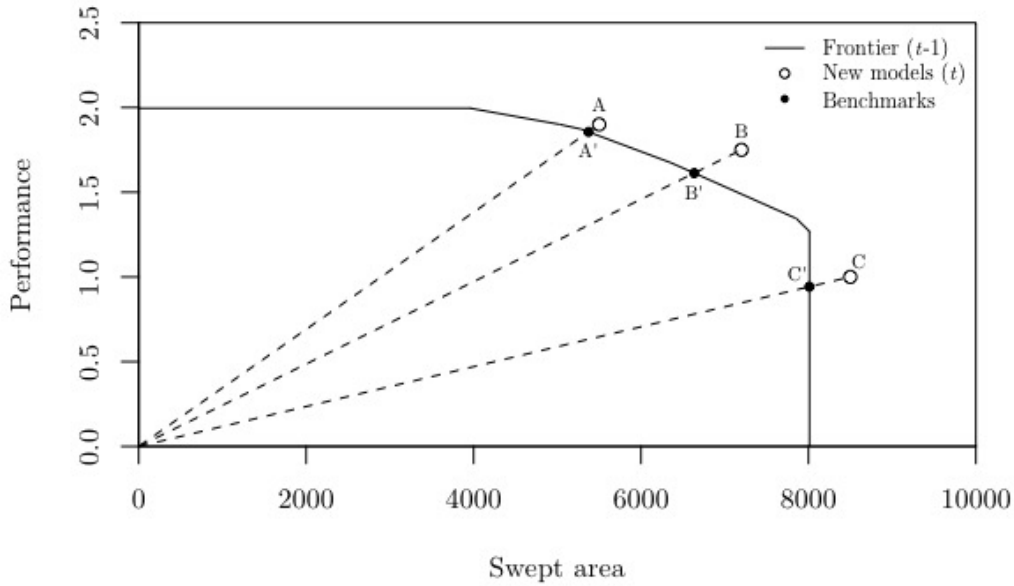


Figure 3.2.3: Contribution based on radial distances

What we first observe is that all three new models lie above the $t - 1$ technology frontier. In order to quantify their contributions, we proceed the same way as done in the DEA method. For instance, the contribution of turbine J is simply:

$$\theta_1^j = \sqrt{\frac{Y_j^2 + X_j^2}{(Y_j')^2 + (X_j')^2}} \quad (3.2.4)$$

where X_j and Y_j are respectively the size and performance levels of turbine J and X_j' and Y_j' stand for the coordinates of the associated benchmark point. The latter is located at the intersection between OJ and the $t - 1$ frontier.

This measure has kind of a discrete interpretation. It translates the ability of one turbine manufacturer to propose a novel combination of characteristics. For instance, model C on Figure 3.2.3 has what could be called a size contribution. Indeed, it has a higher swept area than any model available at $t - 1$. With regard to the θ_1 measure, it is considered to have a positive contribution, despite a relatively low performance level. The contributions of models A and B is more clear: they allow for a higher size (performance) level at a given

performance (size) level. As such, those models allow for a more efficient conversion of a higher amount of kinetic energy than what was possible before.

Contribution measures based on isoquants

We complete the θ_1 contribution measure with a more strict measure based on the so-called *iso-product curves* or *isoquants*. Recall that, from Equation 3.2.3, the product of the two characteristics gives the expected annual energy production of the turbine. Thus, one can draw the isoquants that represent all the possible characteristics combinations that lead to the same amount of electricity production. By doing so, we are able distinguish between “fruitful” and “fruitless” innovations.⁵ Figure 3.2.4 illustrates this fact. What we observe from the isoquant of model C is that the same energy production was reachable at period $t - 1$ for a lower size level (the minimum value of it being X'_C). Such an innovation may be considered as “fruitless” in the sense that the increase in size is not combined with a sufficient performance level to allow for higher electricity production.⁶

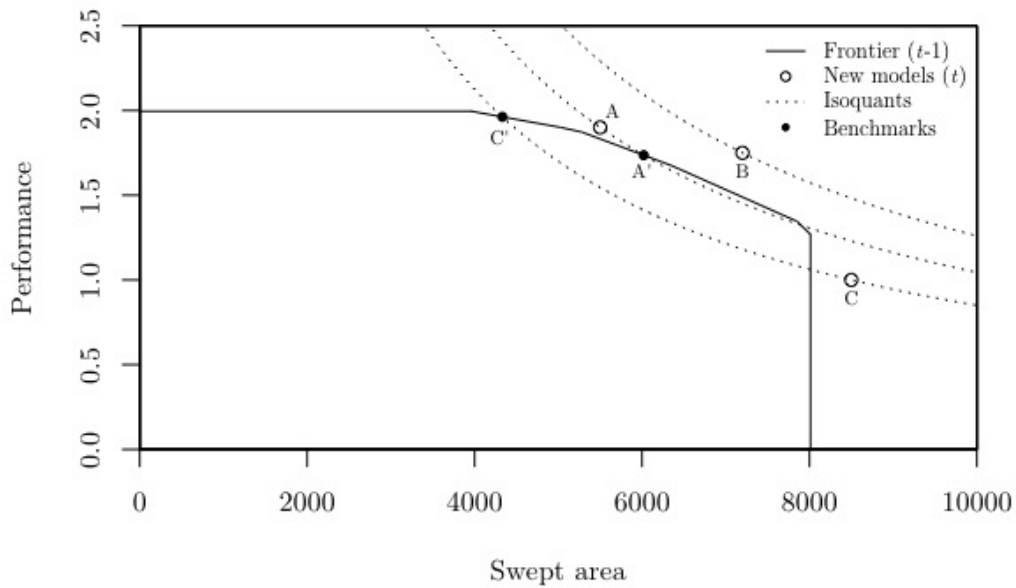


Figure 3.2.4: Contribution based on isoquants

⁵With regard to energy production. Indeed, some technological trajectories are unexplored in this work. For instance, any new model having no contribution based on our measure may for instance have a reduced noise level or be sold at a lower price.

⁶This is especially interesting in light with the so-called *square-cube law* of wind power. This practitioner rule-of-thumb states that a turbine’s absolute power output is proportional to the square of the turbine’s blade length (which is obvious from Equation 3.2.1), but that, at the same time, a blade’s volume and weight – and thus its cost – are proportional to the cube of its length. In other words, the price of a turbine climbs faster than its power output as its size increases. Within this context, decreasing the size of a machine without affecting the electrical output of it is attractive.

In this interpretation, what is considered as a positive contribution is an increase in the absolute energy production level relative to the maximum allowed by the $t - 1$ frontier. This point is labeled AEP_{max} on Figure 3.2.5. Unlike when the θ_1 measure was considered, model B is now the only one to be considered as having a positive contribution to technical change, because its isoquant does not cross the $t - 1$ frontier. This leads us to define the θ_2 measure of contribution such as, for any turbine J

$$\theta_2^j = \frac{X_j Y_j}{X_{max} Y_{max}} \quad (3.2.5)$$

where X_{max} and Y_{max} stand for the coordinates of the $t - 1$ highest production combination.

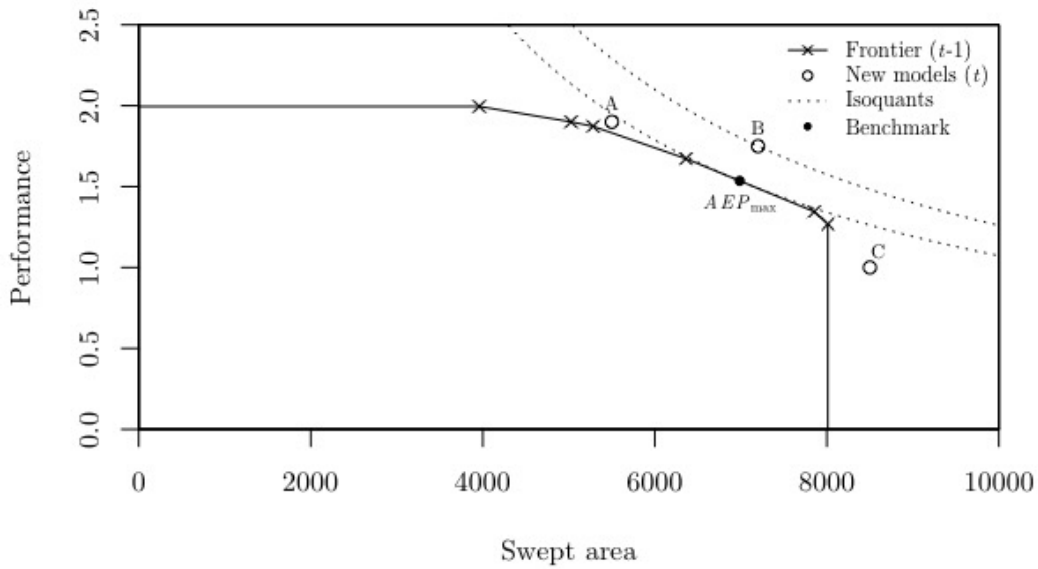


Figure 3.2.5: Contribution to absolute AEP

The variable returns-to-scale DEA method assumes that the frontier is concave, i.e. that every linear combination between two efficient points is reachable. As a consequence, the AEP_{max} benchmark in Figure 3.2.5 do not necessarily match any existing model, but may represent an hypothetical combination instead. As an additional measure, we consider relaxing the concavity assumption by constructing the frontier using the Free Disposal Hull (FDH) method from Deprins et al. (2006). Figure 3.2.6 displays the resulting frontier using the same data as the previous figure.

Within this context, the maximum energy production level is reached by an existing model, still index AEP_{max} on the figure. The θ'_2 contribution is computed in the same way as θ_2 in Equation 3.2.5, the only difference lying in the values of X_{max} and Y_{max} .

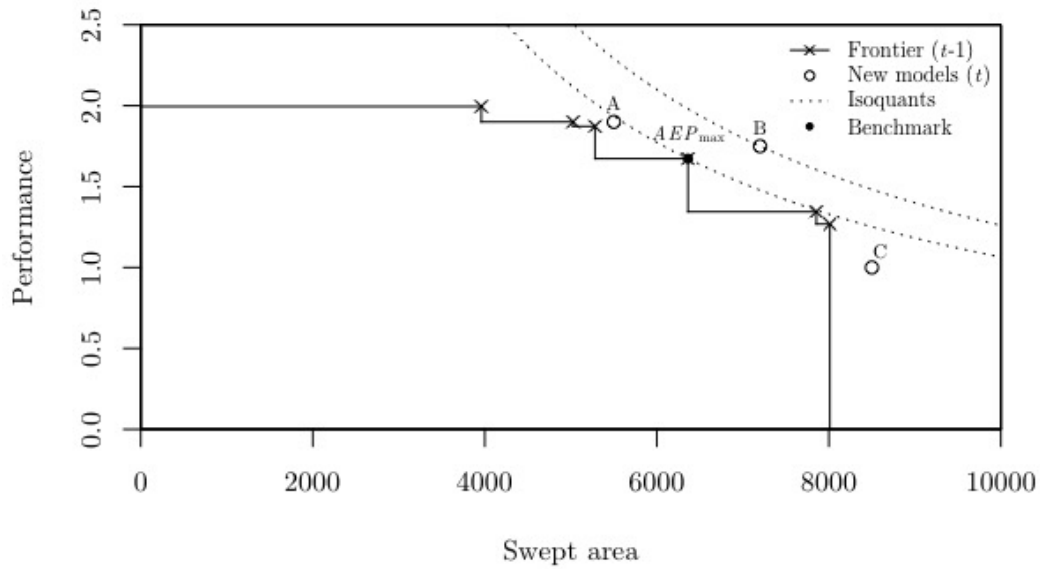


Figure 3.2.6: Contribution to absolute AEP (FDH method)

3.2.3 Data and facts

Data sources

We wish to compute the contribution measures displayed above for each wind turbine model entering the market between 2000 and 2017. To do so, we rely exclusively on data from THEWINDPOWER database. The latter is divided into three distinct files:

- *Turbines* displays information about specific wind turbine models (especially size, rated power, cut-in and cut-off wind speed, year of commercialization...);
- *Power curves* records the power curves of some of the turbines recorded in the *Turbines* part. Production data is available between 0 and 35 m.s⁻¹, by 0.5 m.s⁻¹ bins;
- *Windfarms* records some 28,000 commissioned (or planned) wind parks. It especially displays geographical location, date of commissioning and the specific wind turbine model that is equipped.

For a turbine to be considered in our sample, specific information is required. First, the power curve and the IEC wind class of the turbine must be available in order to compute the expected Annual Energy Production (see subsection 3.2.1). Appendix 3.A provides additional information about the computation of the AEP of turbines in our sample. What is also required to take into account the chronological character of innovation is the year

of commercialization of each turbine. When the information is not directly available in the *Turbines* part of THEWINDPOWER, we use the *Windfarms* part to find the earliest year during which the turbine has been commissioned. Finally, manufacturers that are considered in the sample are those who have been active on the European market. This information is also retrieved from the *Windfarms* file of THEWINDPOWER.

Our final sample consists in 185 wind turbines from 31 distinct manufacturers. 15 additional models are used to construct the initial 1999 frontier. Some information about the main manufacturers composing the sample is displayed in Appendix 3.B.

Illustrations of the frontier analysis

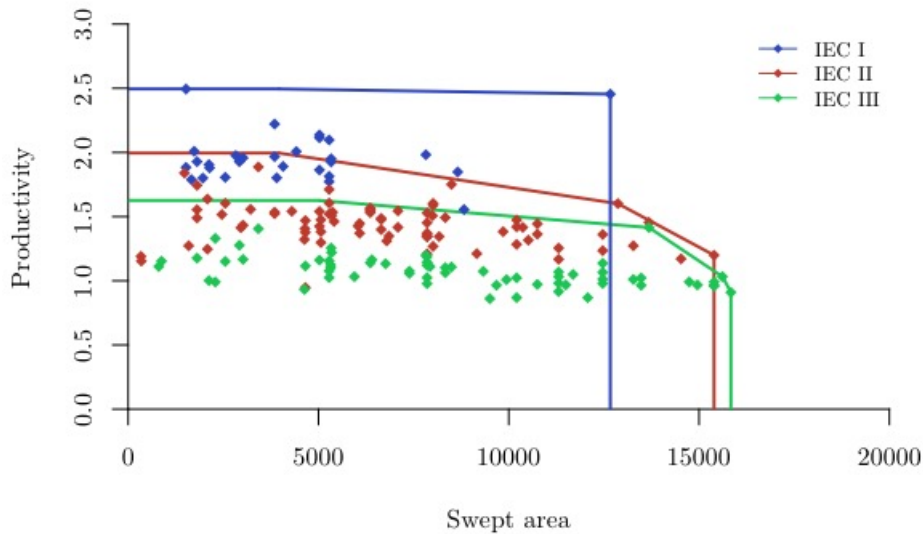


Figure 3.2.7: 2017 frontier, by IEC wind class

Figure 3.2.7 provides three meaningful insights. The figure displays a plot of all turbines in our sample, each of them being defined by a size-performance combination. First, it appears that size and performance are actual substitutes. This is especially striking when focusing on IEC II and III turbines. We observe that the highest performance levels are reached by relatively small turbines, while the latest increases in size have been possible at the cost of a decline in the performance level (see the top-right corners of IEC II and III transformation curves). Second – and related –, we can see that the transformation curve for IEC I turbines has a quite different shape. Indeed, the drawn rectangle reflects the fact that the larger model available has almost reached the absolute maximum value of performance. This is due to the commercialization in 2009 of what is still considered as the world’s highest performing onshore wind turbine, namely the Enercon E126/7500. Following this, the IEC I

frontier has experienced no shift anymore.⁷ One possible explanation for this phenomenon comes from the well-known fact that high-wind sites have become more scarce due to their priority exploitation. This is consistent with the number of new models entering the market along our period of interest, displayed in Figure 3.2.8. One can notice three distinct phases: (i) until 2005, very few low-wind speed turbines enter the market; (ii) between 2005 and 2013, the number of new IEC I models decreases while at the same time, the number of new IEC II and, to a lesser extent, IEC III models increase; and (iii) between 2013 and 2017, IEC III is the more represented category.

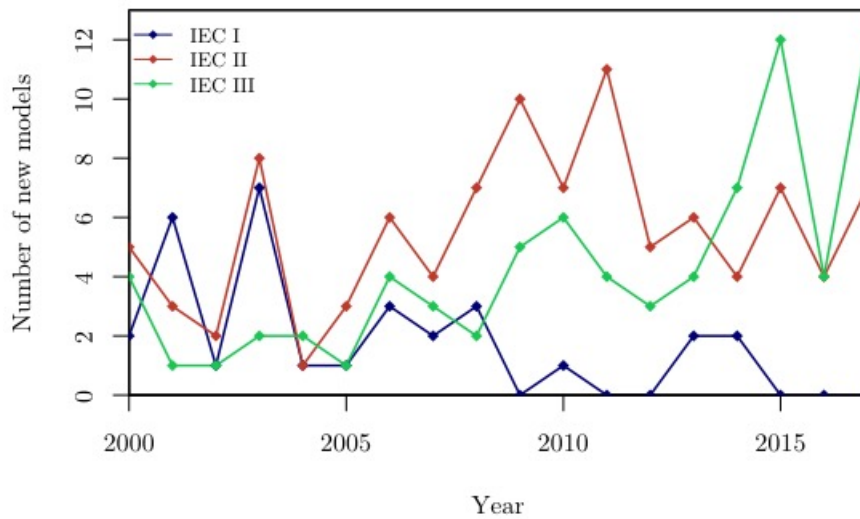


Figure 3.2.8: New models entering the market, by IEC class, 2000-2017

It seems that, consequently, the growing demand for IEC II and III turbines has led to more R&D effort in these classes relative to IEC I class. Finally, another well-known phenomenon that appears in Figure 3.2.7 is the fact that turbine designed for medium and low-wind sites have to compensate this lower wind speed by increasing the amount of wind captured by the rotor. Thus, the frontier for IEC III turbines essentially moves in an horizontal way, reflecting the fact that size is the main lever that low-wind turbine manufacturers can act on to increase the electric output of their machines.

Another point of interest is the chronological evolution of the frontier, displayed in Figure 3.2.9 for medium-wind turbines. For the sake of readability, the evolution is provided by 4 years intervals, but interpretations remain the same as in the case of yearly shifts. We

⁷In fact, what is now considered as the largest onshore wind turbine is the 2017 General Electric 158-4.8 (IEC S, i.e. site-specific), with swept area around 19,606 m². This turbine is not considered in our sample due to the lack of production data, but might have induced an horizontal shift of the frontier.

first observe that IEC III wind turbines frontier has experienced important shifts between years 2000 and 2004. Two first shifts are vertical (see the red points on the left): the turbines in question does not have a contribution to size but allows for a higher performance level for an already existing size level. The third one (see the red point on the right) is what we called an absolute size contribution and has lead the frontier to shift to the right. When compared to the 2012 frontier, the 2016 model represented by the blue left point is kind of a breakthrough. Not only it is able to capture more wind than 2012 models, but it also reaches a higher performance level.

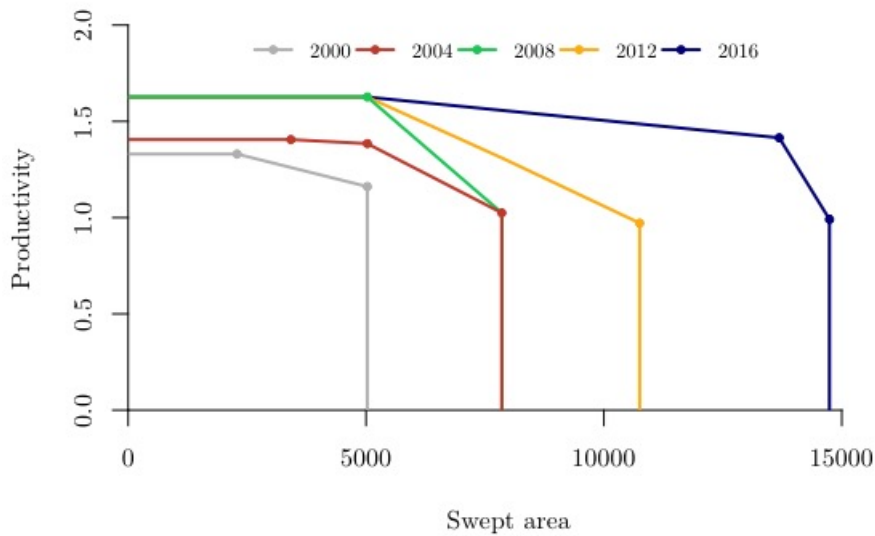
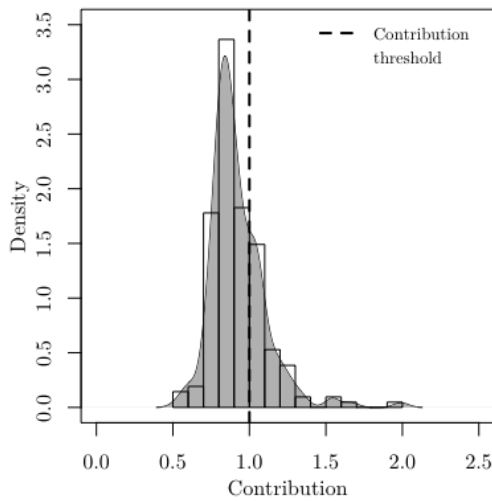
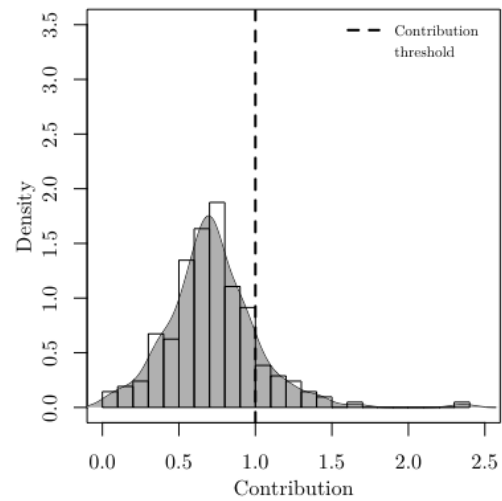


Figure 3.2.9: Evolution of the IEC II wind turbines frontier, 2000-2016

Finally, it is worthwhile to notice that both size and performance innovations have happened during our period of interest. Proceeding this way allows one to take into account the specialization of firms (e.g. on small turbines segment). Indeed, even if most of the top WT manufacturers are involved in a race towards gigantism, some more modest firms are dedicated to the conception of small to medium scale turbines. Moreover, the fact that no turbine has ever raised simultaneously productivity and size in their all-time maximum values is comforting regarding the construction of the frontier.

Figures 3.2.10 and 3.2.11 display the distributions of, resp., θ_1 -type and θ_2 -type contributions in our sample, while Table 3.2.2 provides some summary statistics. What we observe is that θ_2 -type contributions are more strict in the sense that only 26 models are considered to have had a positive θ_2 contribution against 56 positive θ_1 contributions.

Contributions at the firm level

Figure 3.2.10: Distribution of θ_1 measureFigure 3.2.11: Distribution of θ_2 measure

	Min.	Q1	Med.	Mean	Q3	Max.	# pos.	% pos.	N
θ_1	0.531	0.812	0.878	0.923	1.015	1.991	56	26.92	208
θ_2	0.027	0.552	0.702	0.717	0.867	2.356	26	12.5	208
θ'_2	0.027	0.553	0.707	0.720	0.875	2.356	27	12.98	208

Table 3.2.2: Summary statistics

Once computed the contribution measures for each model in our sample, let's observe which firms are the most innovative with regards to these measures.

The bubble chart of Figure 3.2.12 displays information about firms that have contributed to shifting the frontier during the 2000–2017 period. The x -axis displays the contribution rate, i.e. the share of new models by the firm that have had a contribution. The average contribution of these models can be read from the ordinate axis. Finally, the area of circles is proportional to the number of new models commercialized by firms during the period.

One can first notice that only 13 out of 31 WT manufacturers (42%) that have been active between 2000 and 2017 have proposed “innovative” models with regard to the θ_1 measure. Most of them locate at the center of the graph, with contribution rate between 0.25 (XEMC-Darwind) and 0.54 (Nordex) and average contribution between 1.06 (Fuhrländer) and 1.19 (Vestas). Also, when focusing on the top-left corner we observe that some manufacturers' models (e.g. Leitwind) are seldom innovative, but models that are lead to important shifts of the frontier. Reversely, most of Dewind's new models contribute to shifting the frontier to a relatively low extent. The same distinction can be done among large manufacturers. Vestas and Senvion (formerly RePower) have both commercialized 18 models between 2000 and 2018. A quite small part (27%) of the former's models have had contributions, but those

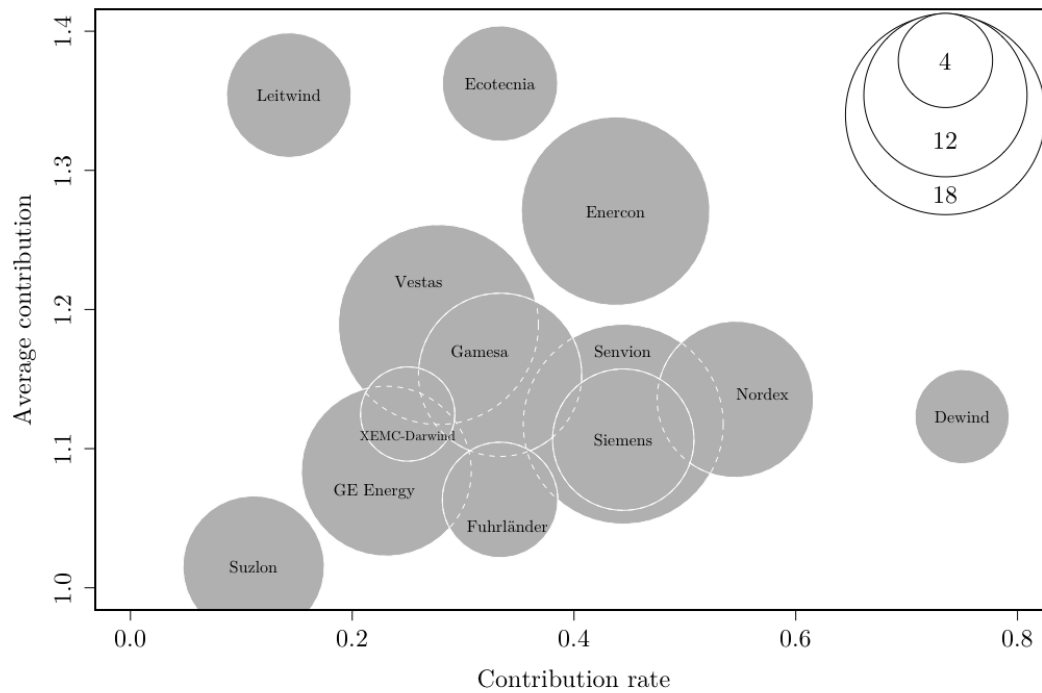


Figure 3.2.12: Summary of firms' contributions over the 2000–2017 period

contributions are quite important (1.19 on average); a larger part of the latter's model have contributed to push the frontier forward (44%), but to a lesser extent (1.11 on average). Maybe the most impressive innovation performance is the one by Enercon. Despite a quite high number of models commercialized during the period (16), the German manufacturer performed well regarding both the contribution rate (44%) and the average contribution extent (1.27). Spanish firm Ecotècnia, that has been active until 2007 then acquired by Alstom, showed interesting performances as well.

3.3 Firms' patent portfolio size *vs* contribution to technical change

3.3.1 Patent counts and the *knowledge stock*

In this section, we show what we considered as relevant patent-based indicators of technical change. This indicator will be confronted to the patent-independent measures presented in the previous section. The main independent variable is the patent portfolio size of the firm at year t .

Wind power related CPC classes

At first, patents entering firms' portfolios are patents recorded in the Y02E 10/7 CPC class (“*Wind power*”) and subclasses. We consider granted patents recorded in the Y02E 10/72 CPC class (and sub-classes, see Table 3.3.1), which concerns the main elements of turbines, the latter being considered to be those that affect the power coefficient. As mentioned in the previous section, our focus is on onshore wind turbine due to data issues; as a consequence, we do not consider patents belonging to the *Offshore towers* sub-class.

Symbol	Classification and description	Selected
Y02E 10/72	Wind turbines with rotation axis in wind direction	✓
Y02E 10/721	Blades or rotors	✓
Y02E 10/722	Components or gearbox	✓
Y02E 10/723	Control of turbines	✓
Y02E 10/725	Generator or configuration	✓
Y02E 10/726	Nacelles	✓
Y02E 10/727	Offshore towers	✗
Y02E 10/728	Onshore towers	✓

Table 3.3.1: Selected CPC classes and associated descriptions

Patent renewals and “up-to-date” portfolio size

Patent portfolios take into account renewals, such as a granted patent k is considered as part of its applicant's portfolio at year t if:

$$\begin{cases} t_{Fk} < t < t_{Lk}, & \text{if lapsed} \\ t_{Fk} < t, & \text{if still “alive”} \end{cases} \quad (3.3.1)$$

with t_{Fk} the application filing year of patent k and t_{Lk} its lapse year.

Patent protection at the EPO begins at application filing date for a maximal duration of 20 years. Thus, we make sure to cover the whole protection period for patents that have effectively been granted by the EPO. The main limitation about it concerns pending applications: at the time of the study, some filed applications may be excluded from their applicant's patent portfolio whereas they will finally translate into patents at a later date. Even if the uncertainty surrounding the so-called grant lag is limited for the involved parties (e.g. applicant, competitors, office engineers), it is hard for us to evaluate the probability that a patent will be granted.⁸ However, using PATSTAT Spring 2021 database and as our

⁸Based on discussions with patent examiners, the idea is that the numerous publications made by the office between the application filing date and the grant decision are informative about that probability. For

period of interest runs until year 2017, the impact of this issue is limited.⁹

Identifying product patents

In this work, we rely on the methodology developed in Chapter 2 to identify “product patents” (i.e. patents covering product inventions). Theoretical contributions have for a long time distinguished between product and process innovation. Usually, product innovation is supposed to affect the characteristics of goods, while process innovation leads to a decrease in the production cost of the same goods. [Cohen and Klepper \(1996b\)](#) consider that both of them lead to a raise in the price-cost margin of the underlying good. In the first case, improvements in the the product characteristics justifies a higher price for it; in the second case, the margin raise is reached through a decrease in the marginal cost of production. As our measure of innovation is exclusively based on technical characteristics (thus neglecting the cost of technology), our study should focus on patents covering product innovations. Ideally, we wish to separate product patents in order to make sure that the selected patents are supposed to translate into technical improvements of the wind power technology. In Chapter 2, we used a continuous measure of the “productness” of patents (hereafter φ) based on a keyword search ([Banholzer et al., 2019](#)). A value of 1 (resp. 0) indicates that the patent only contains product (process) keywords. This measure has the advantage of accounting for “mixed” – i.e. both product and process – patents and translates the weight of the product part in a particular patent.

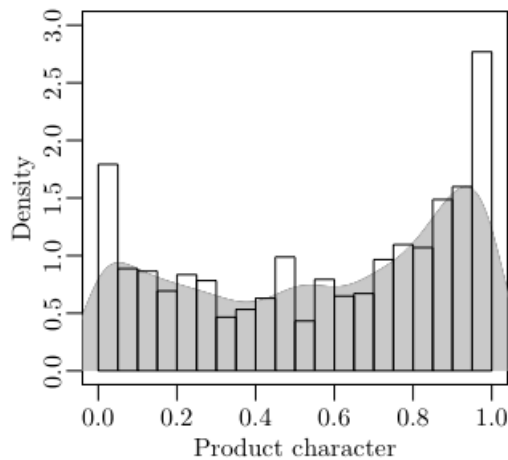


Figure 3.3.1: Distribution of φ in our sample ($N = 5,367$)

instance, the content of the EPO search report provides elements that may drive the expectations of parties toward a rather positive or negative outcome of the application.

⁹The average grant lag in our sample is around 5 years.

Figure 3.3.1 displays the distribution of the “productness” of patents in our sample. One may observe that the distribution is zero and one inflated: a large share of patents are almost “perfect product patents” ($\varphi \geq 0.95$) or “perfect process patents” ($\varphi \leq 0.95$), with respective shares 13.84% and 8.96%. However, there is a quite high number of patents belonging to both categories, which proves the usefulness of relying on a continuous measure of the “productness” of patents.

We thus define the product patent portfolio, PPP_t , as

$$PPP_t = \sum_{k=1}^{N_t} \varphi_k \quad (3.3.2)$$

where N_t is the number of patents held by the firm and being active at year t .

Weighting patent counts using citations data

Using a simple count of patents, one assigns a weight of one to each patent. The main drawback of it comes from the known heterogeneity in patents’ *quality* or *value*. In other words, one patent may protect a breakthrough invention as well as a very incremental one, but it will still be considered as *one* patent. One way to avoid this is to rely on the number of citations a particular patent received. It is considered since (Trajtenberg, 1990) that forward citations provide information about the value of the underlying invention. Moreover, if corrected for self citations, it is a metric that the patent holder itself can not control.

Let’s consider any patent k filed at year t and let C_k be number of citations (excluding self-citations) it received (as recorded in PATSTAT Spring 2021 database). Also, we denote by $\bar{C}_t$ the average number of citations received by patents filed at year t . The forward citation index of patent k is simply:

$$w_k = \frac{C_k}{\bar{C}_t} \quad (3.3.3)$$

Proceeding this way (i.e. considering the number of citations relative to the average number of citations within the same *cohort*) allows us to take into account the fact that patents filed more recently have necessarily received less citations. By construction, the sum of such weights over all patents equals the total number of patents.¹⁰

¹⁰Moreover, one has to notice that we implicitly assume the share of citations made to the “product part” of a patent equals the latter. A more careful analysis would require to estimate the product part of citing patents as well. Such a process being very time consuming at this time, this issue will be the focus of further developments.

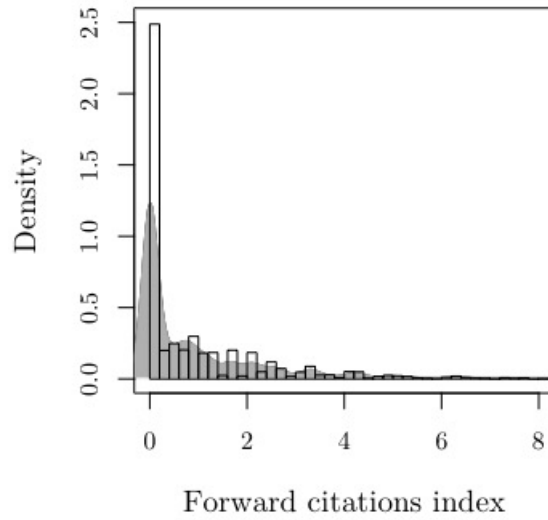


Figure 3.3.2: Distribution of the forward citation index in our sample ($N = 5,367$)

Finally, the value of the weighted portfolio of a given firm at year t is the sum of the forward citations index for each patent k held by the firm and being valid at year t

$$WPPP_t = \sum_{k=1}^{N_t} w_k \times \varphi_k \quad (3.3.4)$$

Figure 3.3.3 highlights the main differences between patent counts in the whole wind power industry. One first observation wind power actors did not rely so much on patent protection until the 2000s. Also, one may notice that a very large share of patents in the wind power industry are renewed. The solid and dashed line confounds until year 2011, at which date some patents begin lapsing. Accounting for the “product character” of patents highlights the fact that product innovation concerns more than 50% of renewed patents.

3.3.2 On the patent – technical change relationship

In this section, we are interested in observing the relationship between actual contributions of firms to technical change and the size of their patent portfolios. Figure 3.3.4 highlights a positive relationship between the number of granted patents and the number of innovative models from firms.

Thus, firms having contributions to the frontier are mostly those holding patents. We also observe some heterogeneity. Interestingly, the ratio between the number of new models and

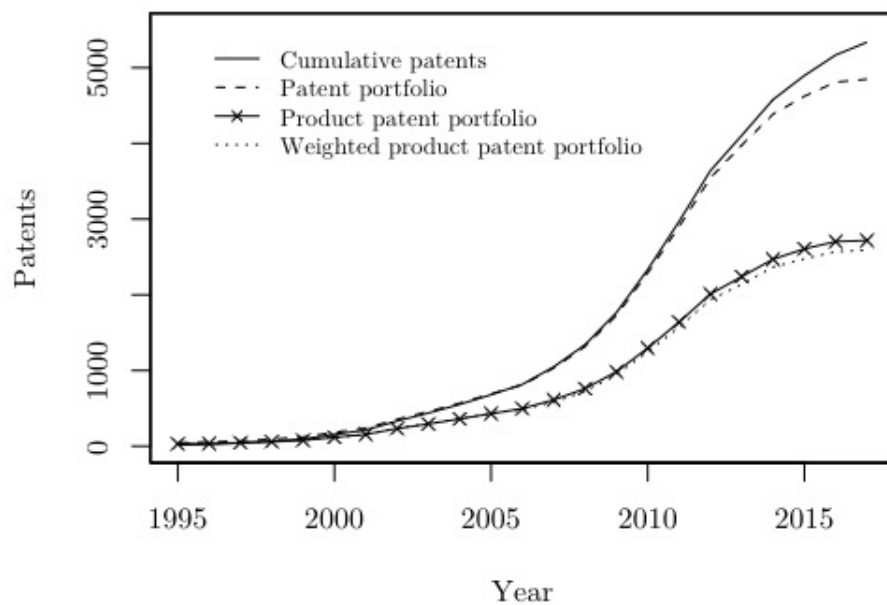


Figure 3.3.3: Knowledge stock estimations

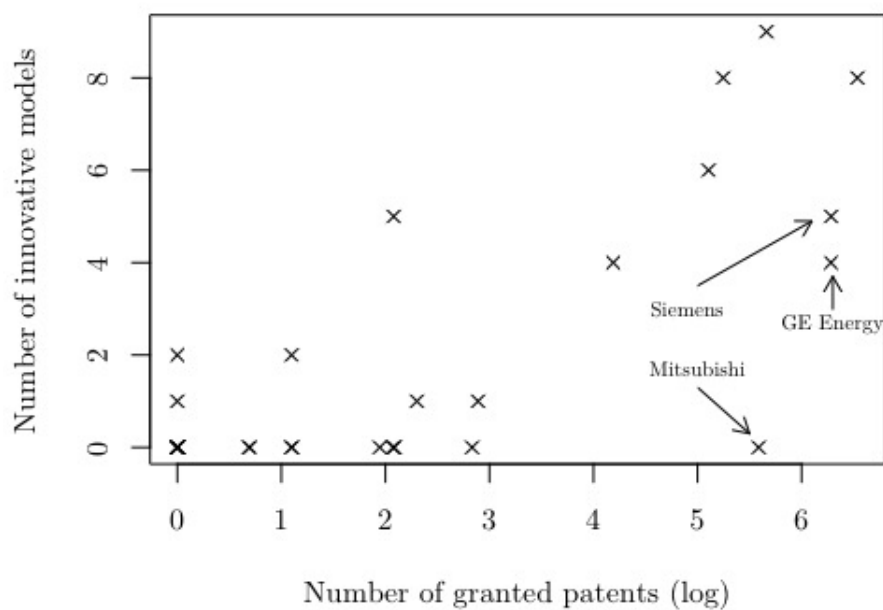


Figure 3.3.4: Correlation between the number of innovative models and the number of granted patents over the 2000-2017 period

the number of granted patents is lower for conglomerates. A possible rationale for this fact is that such companies have more experience in patenting in other various sectors.

We wish to appreciate whether holding patents translates into actual, concrete technical change. We observe, for each firm, the θ^1 and θ^2 contributions of new turbines entering the market as well as evolution in the size of their patent portfolio. We propose using a fixed effects panel regression to account for heterogeneity between firms. Our panel is highly unbalanced due to both the facts that (i) not every manufacturer has commercialized a new turbine each year, and (ii) not every manufacturer has been active during the whole time period. As observed from Figure 3.3.3, relying on patent protection did not seem to be a common practise until the mid 2000s. As an attempt to reduce this effect, we will consider patent portfolio size relative to the average portfolio size at a given year. The main motivation for this comes from the fact that a low number of patents can hide a large representation in the global portfolio. For instance, German manufacturer Enercon used to have some patents before 2000. Even a small number of patents is interesting as the number of patents filed in the whole industry was very low. Using such an index allows one to take into account the representation of firms in the global patent portfolio. Moreover, as the dependent variable in the model is the contribution of firms relative to the industry technology frontier, treating patent counts the same way seems to be relevant.

Also, it is usually accepted that there is a time lapse between patenting a technology and the fact for it to reach the market. Thus, we will consider lagging patent portfolios, until $t - 5$, to observe whether patenting activity translates into technical change only after a certain amount of time. We also include market shares of firms as well as the stringency of the wind power feed-in tariff policy in the home country of firms that might affect the extent of firms' contributions.

Market shares of firms are computed from installed capacities recorded in the THEWIND-POWER database. [Blundell et al. \(1999\)](#) have shown that, within industries, firms with the highest market shares are those which commercialize more innovations. Another finding from them is that increased product market competition in an industry is associated with a higher innovative activity.

Data on feed-in tariffs is retrieved from the OECD database. There is no consensus about the actual impact of feed-in tariffs on innovation in “green” technologies. For instance, [Lin and Chen \(2019\)](#) shows that the implementation of feed-in tariffs have promoted innovation on the Chinese wind power sector. Reversely, [Böhringer et al. \(2017\)](#) and [Schleich et al. \(2017\)](#) do not find any significant impact of the feed-in tariff scheme on innovation in Germany.

The main equation of the model is as follows:

$$C_{i,t} = \beta_1 PC_{i,t-a} + \beta_2 MS_{i,t-b} + \beta_3 POL_{i,t-c} + \alpha_i + \lambda_t + \epsilon_{i,t} \quad (3.3.5)$$

in which α_i and λ_t are resp. firm and year fixed effects. Variable description is displayed in Table 3.3.2.

Variable	Content	Lag	Sub-variable	Content	Source
$C_{i,t}$	Contribution of firm i to technical change at year t	–	–	–	Author’s computation from THEWINDPOWER data
$PC_{i,t-a}$	Normalized patent count of firm i at year $t - a$	$a \in [1, 5]$	P	Simple patent count	Author’s computation from PATSTAT data
			PP	Patent portfolio	
			PPP	Product patent portfolio	
			$WPPP$	Citation-weighted product patent portfolio	
$MS_{i,t-b}$	Market share of firm i at year $t - b$	$b \in [1, 5]$	–	–	Author’s computation from THEWINDPOWER data
$POL_{i,t-c}$	Feed-in tariff policy in firm i ’s country at year $t - c$	$c = 0$	FIT	Mean feed-in tariff	OECD
		$c = 5$	STR	Feed-in tariff stringency index	

Table 3.3.2: Introduction of the variables

In order to find the values of both a and b and to avoid multicollinearity issues, we used a best subset regression method, the main criterion for it being the R^2 value. At the beginning of the process, we considered all the patent counts mentioned in the previous subsection. Also, we restricted the interval for the possible value of a and b to $[1, 5]$. As such, the best fitting model provides information about the relevant patent count as well as the relevant lags to consider.

Results

Table 3.3.3 displays estimation results (standards errors are clustered). For each indicator of innovative performance (θ^1 and θ^2), we provide results for the best fitting model according to the R^2 measure. The left column displays the best fitting model including the mean feed-in tariff in manufacturer i ’s country at year t ($FIT_{i,t}$) while the right column displays the best fitting model including stringency index of the feed-in tariff policy in manufacturer i ’s country at year $t - 5$ ($STR_{i,t-5}$). Finally, the $\text{Max}(\theta)$ stands for the fact that, in cases in which one manufacturer has commercialized several different model of turbines the same year, we only focused on the most “innovative” turbine among them.

We observe that the ability for firms to propose novel combinations of characteristics is significantly and positively correlated with the 4-years lagged patent portfolio size: on average, increasing the portfolio index by 1 translates into a 0.0184 raise in the value of θ^1 four years later. Focusing on the the performance of turbines with regards the power

	<i>Dependent variable:</i>			
	Max(θ_{it}^1)		Max(θ_{it}^2)	
	(1)	(2)	(3)	(4)
$PP_{i,t-4}$	0.0175*** (0.0055)	0.0184*** (0.0043)		
$PPP_{i,t-4}$			0.0270*** (0.0089)	0.0278*** (0.0068)
$MS_{i,t-3}$	-0.0081*** (0.0027)	-0.0075*** (0.0027)	-0.0131*** (0.0042)	-0.0122*** (0.0039)
$FIT_{i,t}$	-0.2834 (0.2378)		-0.6037 (0.3780)	
$STR_{i,t-5}$		0.0113 (0.0075)		0.0271 (0.0166)
Indiv. FE	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes
R^2	0.1033	0.1038	0.0978	0.1017
Observations		114		
N		17		
T		4-18		
<i>Note:</i> * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$				

Table 3.3.3: Best-fitting fixed effects regressions

output of their turbines, we observe that the knowledge stock measure that provides the best fit include the “product character” of patents. In the same vein as for θ^1 , an increase in the product portfolio index translates into a raise in the power output four years later. More specifically, adding an in translates into an increase in θ^2 by 0.028.

In all cases, we observe a negative and significant value for the estimate of β_2 for $b = 3$, indicating a negative correlation between the value of θ^1 and the market share three years before. Interpretation for this may be that the firms seek to stand out from competitors by innovating. This result is confirmed when focusing on the θ^2 measure and goes against those by [Blundell et al. \(1999\)](#) only partially as it is consistent with the idea that competition is a driver of innovation. Finally, the stringency of renewable energy policies in the domestic country of firms does not appear to be a driver of technical change, which is quite consistent with the related literature.

Table 3.3.4 displays the fixed effects from model (2) for the 7 main players in the European wind turbine market. It allows one appreciate the heterogeneity between firms and tends to confirm the fact that conglomerates’ large patent portfolios do not translate into particularly innovative turbines. Indeed, the fixed effects are higher (≥ 1) for wind power specialists

	Enercon	Gamesa	GE Energy	Nordex	Senvion	Siemens	Vestas
FE	1.051	1.015	0.841	1.000	1.045	0.9211	1.091

Table 3.3.4: Estimated fixed effects for model (2)

than those of conglomerates GE and Siemens.

Figure 3.3.5 displays time series for the evolution in the 4-years lagged patent portfolio index ($PPP_{i,t-4}$, dashed line) and the contributions of new models to the energy output frontier ($\theta_{i,t}^2$, solid line) for the 7 main WT manufacturers in the European market. The x -axis displays periods. Each period corresponds to a year at which a new model from the firm entered the market. The associated years are indicated right below.

Something interesting to observe from this figure is that, at early periods, some manufacturers have had important contributions to technical change at times when they did not held any patent yet, or very few of them. Good examples for this fact are those of Nordex, Senvion or Vestas.¹¹ Figure 3.3.6 displays the evolution in the annual onshore installed capacity and number of patents in Europe from 1990 to 2017. Installed capacity is an estimation based on data from THEWINDPOWER database. The number of patents includes patents recorded in the technological sub-classes mentioned in the previous sub-section. Only patents that have been granted afterwards are considered here, and the displayed year is the application year. This partially explains the important decrease in the count from year 2012.¹²

Figure 3.3.6 suggests that patenting activity by wind power firms have followed the demand for turbines. Indeed, we observe that the installed capacity has experienced an important raise from the mid-1990s while patenting activity is enhanced at the beginning of the 2000s. This suggests that patents in this sector may have been used for securing rents. If so, and in the light of our results, such behaviours have not had an harmful effect on innovation. This would suggest that the European patent system is an efficient tool to promote innovation.

The solid line of Figure 3.3.7 displays the evolution in the Herfindahl-Hirschmann index (HHI) on the European onshore wind turbines market, computed from THEWINDPOWER data. First, we observe a quite low concentration level at the end of the 1990s. From this point in time, the HHI starts growing until flirting with the 2000 threshold from year 2013.

¹¹For instance, Danish company Vestas Wind System is active since year 1979 but has filed her first patent in 1999 at the Danish Patent and Trademark Office.

¹²However, the decrease in the number of wind power related patent applications has already been documented.

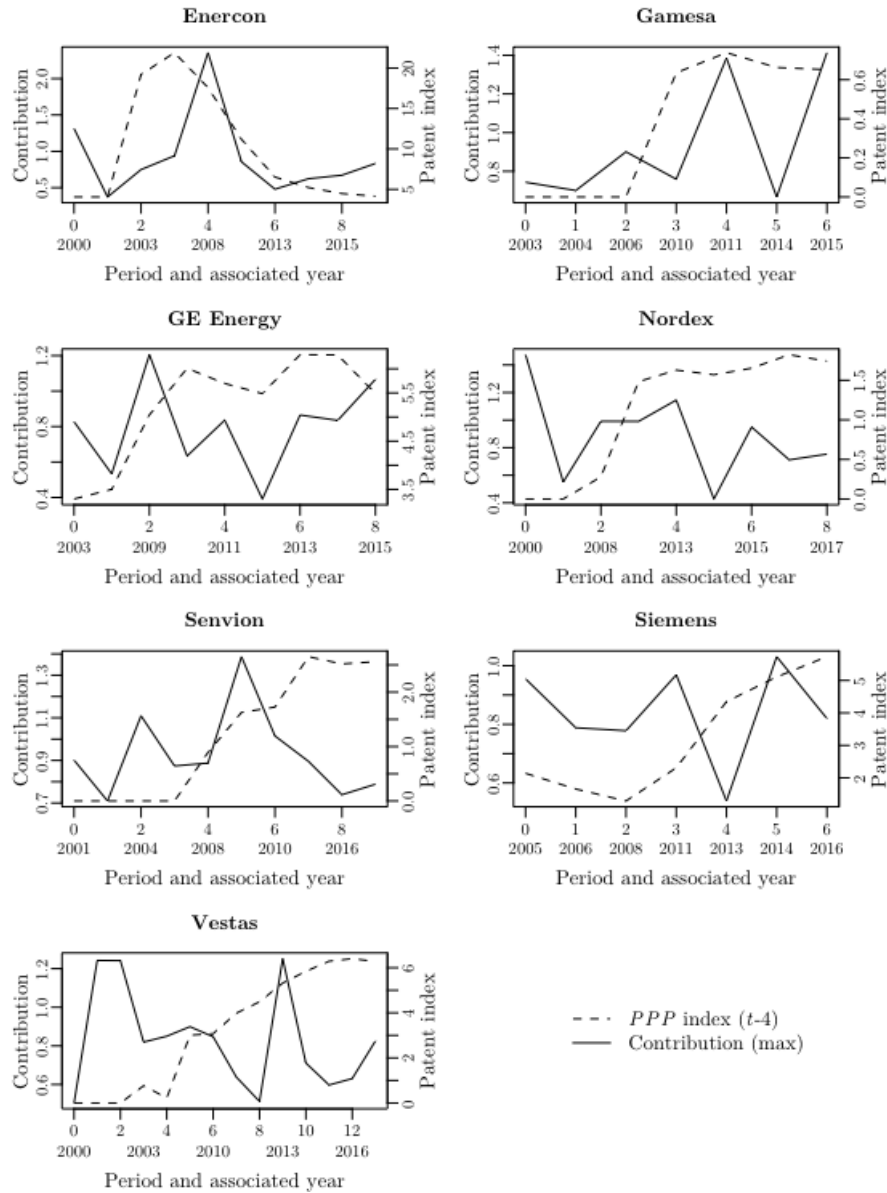


Figure 3.3.5: Patent portfolios and contributions to technical change

This timeline suggests that patenting activity has not been a driver of market concentration since the raise in the HHI index has been enhanced prior to the significant increase in patenting activity experienced by the sector at the beginning of the 2000s. Second, no co-evolution seems to appear between the value of the HHI and the maximum contribution level (dashed line). The latter reflects global changes in the wind turbines technology frontier. We already noticed that (i) there is a negative correlation between market share and contribution to technical change, and (ii) conglomerates, despite holding more patents, are not especially active in pushing the frontier forward. Put together, these three elements cast some doubt about the so-called *Schumpeterian hypothesis*, according to which innovation is driven by market power.

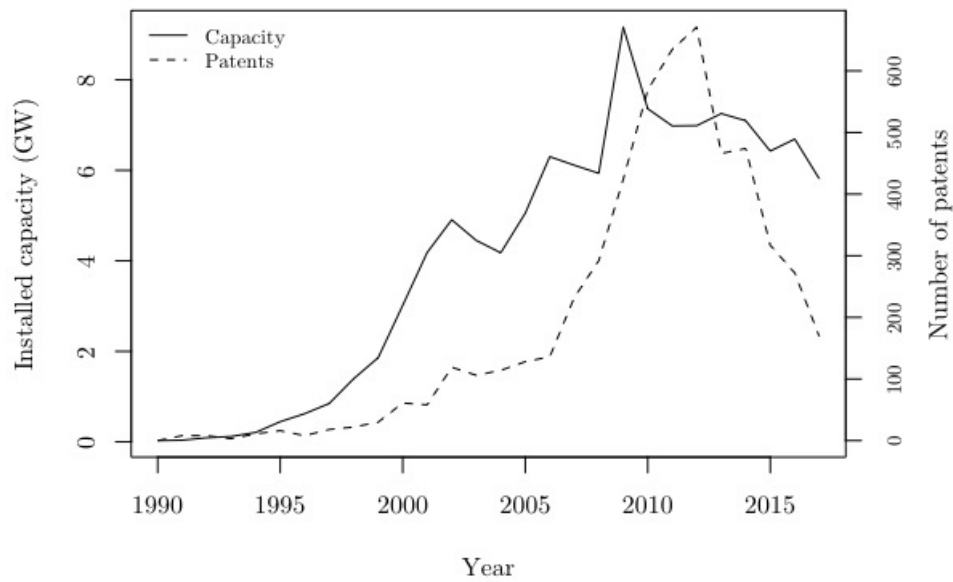


Figure 3.3.6: Evolution in the installed capacity and in the number of patents, 1990-2017

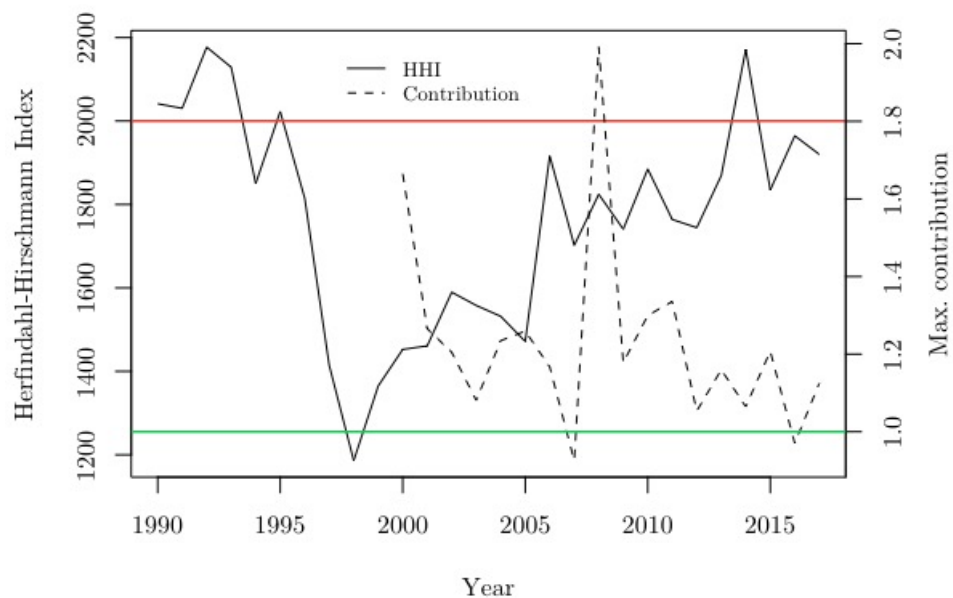


Figure 3.3.7: Evolution in the HHI and maximum contributions on the European onshore wind turbines market, 1990-2017

Notes: shift(s) in the technology frontier have occurred if the maximum contribution value is above 1 (green line). The red line stands for the HHI threshold usually relied on to define a concentrated market.

3.4 Conclusion

The main objective of this paper was to shed some light on the relationship between patents and technical change. Our approach, based on an objective, patent-independent measure

of contribution to technical change by wind turbine manufacturers, has allowed us to draw some conclusions about the effectiveness of the European patent system in spurring innovation in the onshore wind power industry.

First, we observed that, before the mid-2000s, shifts in the frontier have happened despite a low patenting activity in the wind power sector. After this period, we observed that manufacturers pushing the frontier forward are mostly those holding patents. This is confirmed by econometric results: a high representation in the global patent portfolio is associated with higher turbine performance. However, taking into account the heterogeneity between firms has led us to conclude that conglomerates active in the wind turbine industry hold more patents than the average while not proposing significant improvements in the technology with regard to our measures. This might be a signal for the presence of rent-seeking strategies. However, it appears that the growing patenting activity from the beginning of the 2000s has followed simultaneous raises in the demand for turbines and the market concentration instead of being a driver of the latter. Thus, this work supports the fact that the European patent system provides an incentive to innovate while not overly hampering competition.

Patent counts are positively associated with innovative performance when patenting activity in the underlying sector is accounted for. This is an important message regarding the use of patent data as a proxy for the innovative activity of firms and the assessment of patent's value. Indeed, it appears that accounting for renewals is key to apprehend actual technical change as up-to-date portfolios provided the best fit with a patent-independent measure of technical change. In contrast, relying on a forward citations weighting scheme do not provide substantial additional information. Finally, we also showed that considering the product patent portfolio may be insightful. In the present case, we found this measure to be the better proxy for the ability of new turbines to produce more energy. Finally, our results also suggest that the average time-to-market lag is about four years. Such an element is also to be borne in mind when studying innovation based on patent data.

Appendices of Chapter 3

Appendix 3.A Computing the Annual Energy Production (*AEP*)

Based on the IEC class for which one turbine is designed, we approximate the wind speed distribution at hub height using a Rayleigh distribution, which is commonly used in meteorology¹³. The probability density function of wind speed V is given by

$$f(V; \sigma) = \frac{V}{\sigma^2} e^{-V^2/(2\sigma^2)} \quad (3.A.1)$$

with σ the scale parameter of the distribution.

The mean of a Rayleigh-distributed random variable V is given by

$$\mu(V) = \sigma \sqrt{\frac{\pi}{2}} \quad (3.A.2)$$

Estimating the wind speed distribution using the Rayleigh distribution only requires information about the mean wind speed $\bar{v}$. We thus have the following p.d.f

$$f(V) = \frac{\pi}{2} \frac{V}{\bar{v}^2} e^{\left[-\frac{\pi}{4} \frac{V^2}{\bar{v}^2}\right]} \quad (3.A.3)$$

And the c.d.f. is given by

$$F(V) = 1 - e^{\left[-\frac{\pi}{4} \frac{V^2}{\bar{v}^2}\right]} \quad (3.A.4)$$

¹³Data about actual wind speed can be used to fit a Weibull distribution. When no such data is available, one can rely on the Rayleigh distribution which is a particular case of the Weibull distribution where the shape parameter k equals 2. Finally, the only required parameter is the average wind speed, which is provided by the IEC standard.

As turbines are designed for specific wind classes defined by the IEC standard, mean wind speed $\bar{v}$ can easily be derived from IEC classes' average wind speeds. Mean wind speeds for IEC classes are displayed in Table 3.A.1.

Wind class	Average wind speed at hub height (m.s^{-1})
IEC I	10
IEC II	8.5
IEC III	7.5

Table 3.A.1: IEC wind classes and associated average wind speeds

The association of a turbine's power curve with its associated Rayleigh distribution allows one to estimate a theoretical *AEP* (Annual Energy Production)¹⁴, which is calculated as

$$AEP = T \cdot \int_{V_{ci}}^{V_{co}} [(f(V) \times P(V))] dV \quad (3.A.5)$$

where $T = 8,760$ is the number of hours per year, $f(V)$ the wind speed p.d.f., $P(V)$ the wind turbine power curve (in W) and V_{ci} and V_{co} are resp. cut-in and cut-off wind speeds.

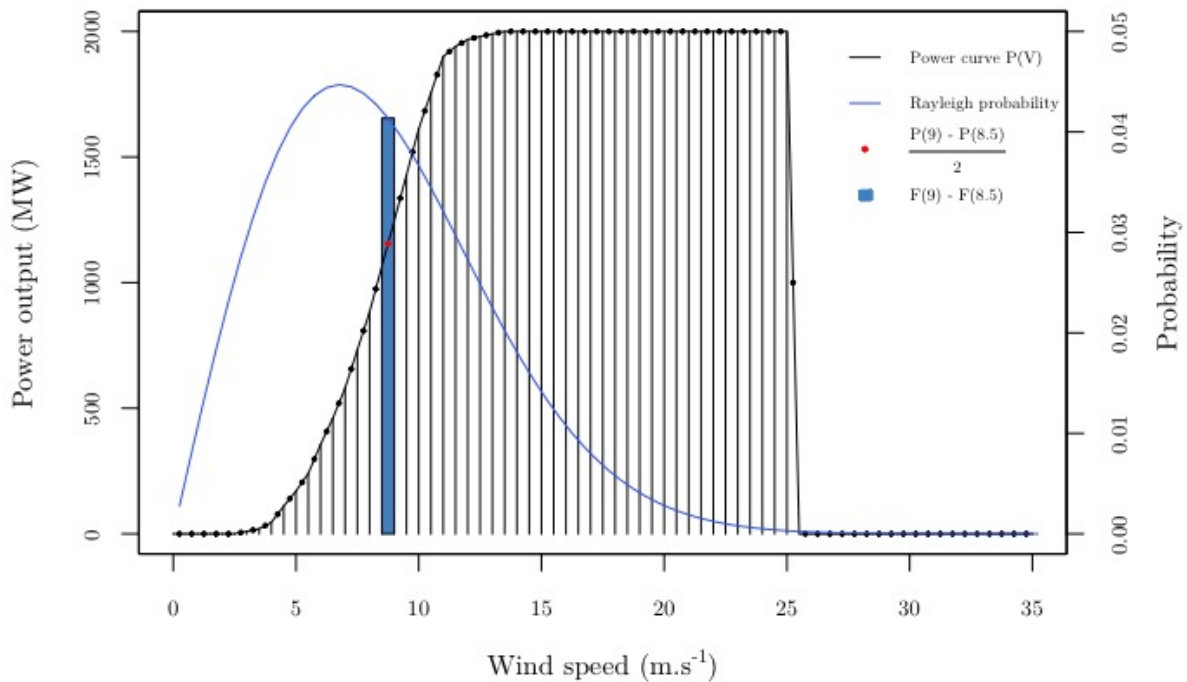


Figure 3.A.1: AEP computation for the Vestas V90/2000 IEC II wind turbine model

¹⁴The main hypothesis behind it is a 100% availability of the turbine (i.e. no maintenance).

Appendix 3.B Main manufacturers considered in our sample

Manufacturer	Country	Beginning year	Beginning acquisition	End year	End acquisition	New models	Actual new models
Vestas	DK	1979	-	-	-	18	24
Enercon	DE	1984	-	-	-	16	18
Senvion	DE	2001	-	2019	S/G	18	21
Siemens	DE	2004	Bonus	2016	S/G	9	11
GE Energy	US	2002	Enron	-	-	13	14
Nordex	DE	1985	-	-	-	11	12
Gamesa	ES	1994	-	2016	S/G	12	13
Goldwind	CN	1998	-	-	-	8	9
Sinovel	CN	2005	-	-	-	3	6
Suzlon	IN	1995	-	-	-	9	9
Vensys	DE	2000	-	2008	Goldwind	7	7
Dewind	DE	1995	-	2017	-	4	7
e.n.o. energy	DE	2008	-	-	-	5	5
Ecotecnia	ES	1987	-	2007	Alstom	6	6
EWT	NL	2004	-	-	-	4	4
Fuhrländer	DE	1991	-	2013	-	6	6
Leitwind	IT	2003	-	-	-	7	7
Mitsubishi	JP	1980	-	2014	-	7	7

Table 3.B.1: Main wind turbine manufacturers

Notes: S/G stands for Siemens-Gamesa, result of the merger of the two eponymous companies. “Beginning acquisition” is the name of the firm that the firm of interest acquired to enter the market. “End acquisition” gives the firm that acquired the firm of interest at “End year”. “Actual new models” takes into account the fact that one unique model may be represented in different IEC classes.

* * *

Chapter 4

Patents, process innovation and the cost of wind turbines: A first look

* * *

The present chapter aims at exploring the relationship between patent counts and the cost of technology in the wind power sector. In this objective, we use information about the choice of a turbine manufacturer by European wind park developers. Especially, we rely on a conditional *logit* model in which a developer selects the turbine that provides her with the highest profit. Technical characteristics of turbines are accounted for and it is considered that the unobservables encompass differences in the price charged by manufacturers. We observe a coevolution between process patent portfolios and the effect of the unobservables over time. The fact that firms undertaking process innovation efforts are more likely to be chosen suggests that patents are useful in promoting process innovation.

* * *

4.1 Introduction

CONFRONTING patent data with patent-independent measures of technical change is worthwhile as a large number of papers study innovation through the prism of patents. This makes sense as, as long the content of patents is public by nature, data availability follows on. Moreover, patents can be seen as the output of the innovation process and might, to some extent, be preferred to data on R&D expenditure that encompasses the inherent uncertainty of this very same process. When it comes to innovation in renewable energy systems, assessing the “direction” of technical change – mainly in reaction to the implementation of environmental policies –, data on patents has proven useful. For instance, one question that has been addressed is whether a feed-in tariff policy is a good instrument to enhance innovation in the targeted “green energies”. The implementation in 2013 of the Cooperative Patent Classification (CPC) by both the European Patent Office (EPO) and the United States Patent and Trademark Office (USPTO) has made the identification of these “green” patents easier by recording them in the dedicated Y class and sub-classes. Consequently, many studies have made use of patent count to analyze the effects of environmental policies (see, for instance, [Johnstone et al., 2010](#); [Lindman and Söderholm, 2016](#)). The recent joint publication by the International Energy Agency and the EPO ([IEA, 2021](#)) is a good example of this as well.

Nevertheless, relying on patent data to reflect technical change is undermined by two well-known flaws. First, not all inventions are subject to patent protection. Indeed, protection against imitation might be reached by trade secret as well, if not more efficiently (mainly when reverse engineering is intricate). Second, there is an heterogeneity in the “quality” or “value” of patented inventions. If some metrics (e.g. forward citations) have been used to weight patent counts to take this into account, there has been few evidence since [Trajtenberg \(1990\)](#) that such measures are appropriate proxies of actual technical advances. In this context, it is thus worthwhile to study the relationship between patent counts and objective, patent-independent measures of technical change. Also, from a policy point of view, analyzing this relationship can provide information about the efficiency of the patent system in fostering innovation. Critics of the patent system consider that the latter, while aiming at spurring research investments, reversely represents a hurdle to innovation. Indeed, patenting strategies may aim at preventing technology advances from competitors rather than differentiating with a cheaper or more efficient product.

It is usually considered that process innovation affects the costs of production while product innovation translates into improvements in the characteristics of the good. If this distinction

has been highlighted for a long time in the theoretical literature,¹ the empirical literature lacks ready-to-use data to allow for such a distinction. In this paper, we propose an attempt to assess how well patent information performs in indirectly revealing the process innovation process. It is believed since [Cohen et al. \(2000\)](#) that patents are best suited to protect product innovations than process innovations. This is due to the fact that the latter are less subject to public scrutiny and thus can be kept secret in an easier manner. While this result is based on a survey of around 1,500 U.S. firms, the present study assesses the relationship between patent counts and process innovation based on objective instead of declarative data. For this purpose, the paper more precisely relies on the detection of keywords in the full text of patents and on modeling the choice of a particular wind turbine manufacturer.

Our analysis focuses on a specific sector, namely wind power. It is indeed an important industry since renewable energy technologies are expected to play an important role in addressing the climate change issue. Also, the focus is on the European onshore wind power. Onshore wind has developed quite early in Europe. First, Europe is considered by competition authorities as the relevant market for wind power.² Second, the time dimension is important here since studying process innovation relates to the theory of learning curves. The latter originates in the seminal work of [Wright \(1936\)](#) and emphasizes that experience affects the cost of technologies.³ Onshore wind power in Europe provides a sufficient hindsight that is required in order to conduct a proper study on technology cost. However, one main obstacle comes from the fact that the price of a turbine is not directly displayed by manufacturers. While some pieces of information can be retrieved from manufacturers' annual reports, not all firms are willing to disclose such figures.

This latter point constitutes the main difference with the work of [Trajtenberg \(1990\)](#). Indeed, based on the set of Commuted Tomography scanners available at a given year, the author computes the evolution in welfare over time. He shows that this evolution is correlated with the evolution in the number of patents in the field and, more specifically, with forward (i.e. received) citations weighted patent counts. In addition to technical characteristics of those scanners, that are included in a choice model through hedonic functions, he has information on prices that is key to a welfare analysis. However, while he is able to compute welfare variation associated with a change in the set of available products, the

¹For instance, [Cohen and Klepper \(1996a\)](#) consider that product innovation allows firms to raise price-cost margin by proposing a more efficient product and charge a higher price for it. Process innovation makes possible an increase in the price-cost margin by lowering the marginal cost of production.

²The European Commission M.8134 case, that deals with the 2016 Siemens-Gamesa merger, is a good example of this.

³See for instance [Ek and Söderholm \(2010\)](#) and [Lindman and Söderholm \(2012\)](#) for an analysis of learning effects in the wind power industry.

analysis remains at a macro level and no information is provided about differences in the behavior of firms. Here, we use information on wind turbine choice and technical characteristics of turbines to infer differences in the prices charged by firms to check whether firms holding patents are driving the cost of technology down.

By lowering the production cost of a good, process innovation confers the innovator with an advantage since it should be able, all characteristics being equal, to set a lower price for it and, consequently, increase its market share. Relying on this assumption, and in the absence of cost data, we use information on firms' market share in the wind power industry and their change through time to capture the dynamics in the preferences for wind turbine (WT) manufacturers. By controlling for the technical characteristics of turbines, we consider that the effect of time encompasses improvements that are not captured through observable characteristics. These improvements typically include process innovations, but may also include product innovations that are not captured by observed characteristics as well as organizational innovations. We rely on an original measure of the “processness” of patents, introduced in Chapter 2, to check whether these differences may be imputed to process innovation efforts from firms. Without providing proper evidence that process innovation is a driver of the choice of a wind turbine, our results suggest that, *ceteris paribus*, firms undertaking process innovation efforts are rewarded with increased market shares.

The paper is organized as follows. Section 4.2 provides the economic rationale for the choice of a wind turbine. Section 4.3 presents data mobilized in the paper and their handling. Section 4.4 discusses the econometric specification of the choice model that is used to retrieve the impact of unobservables on the probability of selecting one particular manufacturer. Section 4.5 discusses the results and relates the estimated information with patent counts. Section 4.6 concludes.

4.2 The choice of a wind turbine: theoretical elements

In this section, we propose a very simple model of wind turbine selection that will serve as a basis to the empirical part of the paper. We consider that the relevant criterion for the choice of a turbine is the Net Present Value (*NPV*, π in the following). Wind farm i 's developer⁴ chooses among a set of competing turbines the model j that maximizes the NPV of his investment. This NPV may be written as:

⁴In the following, it is considered that each wind park is supposed to be commissioned by a different developer. Consequently, i equivalently refers to a park or its developer.

$$\pi_{ij} = -I_j + \sum_{t=1}^T \frac{CF_{ijt}}{(1+r)^t} \quad (4.2.1)$$

where I_j is the initial investment cost that we first consider to be the price of wind turbine j ,⁵ r denotes the discount rate and CF_{ijt} is the cash flow resulting from the exploitation of turbine j on site i at year t . It can be decomposed as follows:

$$CF_{ijt} = R_{ijt} - C_{ijt} \quad (4.2.2)$$

where R_{ijt} is the expected revenue from the exploitation of turbine j on site i at year t , C_{ijt} is the corresponding expected operation (O&M) cost. The R_{ijt} and C_{ijt} components both depend on the amount of electricity produced. R_{ijt} is itself decomposed as:

$$R_{ijt} = AEP_{ijt} \times p_{it} \quad (4.2.3)$$

where AEP_{ijt} is the annual energy production of turbine j on site i at year t and p_{it} the electricity price at year t in park i 's country. C_{ijt} is given by

$$C_{ijt} = AEP_{ijt} \times c_j \quad (4.2.4)$$

where c_j is the time-invariant unit O&M cost by kWh produced for manufacturer j .

By setting expected cash flows constant along the lifetime of the project, i.e. assuming no decrease in the turbine's production over time and no upward or downward trend in the dynamics of the electricity price,⁶ we have:

$$CF_{ijt} = CF_{ij} = R_{ij} - C_{ij} \quad (4.2.5)$$

With p_i the electricity price in park i 's country at commissioning year, substituting in Eq. 4.2.1 gives:

⁵It is usually considered that the the price of turbines represents nearly 70% of the total investment cost. Nonetheless, we can expect heterogeneity across parks with regard to this share: for instance, transportation costs will be higher in remote areas.

⁶This is consistent with the existence, in most European countries, of feed-in tariffs. The latter aim at providing electricity price certainty through long-term purchasing contracts.

$$\begin{aligned}
\pi_{ij} &= \sum_{t=1}^T \frac{R_{ij} - C_{ij}}{(1+r)^t} - I_j \\
&= \sum_{t=1}^T \frac{AEP_{ij}(p_i - c)}{(1+r)^t} - I_j \\
\pi_{ij} &= AEP_{ij}p_i \sum_{t=1}^T \frac{1}{(1+r)^t} + AEP_{ij} \sum_{t=1}^T \frac{c_j}{(1+r)^t} - I_j
\end{aligned} \tag{4.2.6}$$

Wind turbines are subject to the wind power square-cube law, that states that the price of a turbine grows faster than the power output of it as rotor size increases. This is mostly due to the mass of material that is required (Jamieson, 2018). The I_j component can thus be divided into an observed part $C(D_j)$ and an unobserved part A_j :

$$I_j = C(D_j) + A_j, \text{ with } \frac{dC(D_j)}{dD_j} > 0 \tag{4.2.7}$$

where D_j is the rotor size of turbine j – such that $C(D_j)$ reflects the square-cube law of wind power – and A_j encompasses all other factors affecting turbine j 's price, including the output of process innovation efforts. The *NPV* of commissioning turbine j in park i can be written as:

$$\pi_{ij} = AEP_{ij}p_i \sum_{t=1}^T \frac{1}{(1+r)^t} + AEP_{ij} \sum_{t=1}^T \frac{c_j}{(1+r)^t} - C(D_j) - A_j \tag{4.2.8}$$

Finally, simplifying notations and assuming a linear relationship between rotor size and the turbine's price yields:

$$\pi_{ij} = R_{ij}\beta^1 + AEP_{ij}\beta_2^j - \beta_3 D_j - A_j \tag{4.2.9}$$

The differentiated β_2^j parameters are meant to capture differences between manufacturers with respect to O&M costs (c_j in Eq. 4.2.8). A_j is a manufacturer-specific component and stands for the unobserved part of profit that the remainder of the paper attempts to infer.

4.3 Data collection and processing

Observed variables in Eq. 4.2.8 are the expected Annual Energy Production for any model j on any site i (AEP_{ij}) as well as the actual average wholesale price of electricity at year t in park i 's country. Data on prices of electricity are data from the European Commission.

Computing the AEP_{ij} values requires processing data from diverse sources. This process is described below. References on technical aspects of wind power include Masters (2013), Hau (2013) and Jamieson (2018).

Computing the expected Annual Energy Production (AEP): some basic physics

The computation of the expected AEP of turbine j on site i requires data on the power curve of turbine j and the distribution of wind speeds on site i .

The power curve of a turbine is defined by the following equation:

$$P(V) = \underbrace{\frac{1}{2} \times \rho \times \pi \times \left(\frac{D}{2}\right)^2}_{P_w(V)} \times V^3 \times C_p(V) \quad (4.3.1)$$

where V is the wind speed (in m.s^{-1}), $P(V)$ the power output associated with wind speed V (in W), D the rotor diameter (in m), ρ the density of air (in kg.m^{-3}), $C_p(V)$ the power coefficient associated with wind speed V and $P_w(V)$ the amount of wind energy captured by the rotor at wind speed V (in W).

Based on the average wind speed on a specific site, we approximate the wind speed distribution at hub height using a Rayleigh distribution, which is quite commonly used in meteorology.⁷ The probability density function is given by

$$f(V; \sigma) = \frac{V}{\sigma^2} e^{-V^2/(2\sigma^2)} \quad (4.3.2)$$

with σ the scale parameter of the distribution.

The mean of a Rayleigh-distributed random variable V is given by

$$\mu(X) = \sigma \sqrt{\frac{\pi}{2}} \quad (4.3.3)$$

Estimating the wind speed distribution using the Rayleigh distribution only requires information about the observed mean wind speed $\bar{v}$. We thus have the following p.d.f

$$f(V) = \frac{\pi V}{2 \bar{v}^2} e^{\left[-\frac{\pi}{4} \left(\frac{V}{\bar{v}}\right)^2\right]} \quad (4.3.4)$$

And the c.d.f. is given by

⁷Data about actual wind speed can be used to fit a Weibull distribution. When no such data is available, one can rely on the Rayleigh distribution which is a particular case of the Weibull distribution where the shape parameter k equals 2. Finally, the only required parameter is the average wind speed.

$$F(V) = 1 - e^{\left[-\frac{\pi}{4}\left(\frac{V}{v}\right)^2\right]} \quad (4.3.5)$$

Increasing the turbine's tower height increases electricity production as wind is supposed to blow faster at higher altitudes. The relation between the two variables can be approximated using the wind velocity gradient's power law, such as

$$V(h) = V_{ref} \times \left(\frac{h}{h_{ref}}\right)^\alpha \quad (4.3.6)$$

where h is the turbine's tower height, V_{ref} is the wind speed at reference altitude h_{ref} and α is the so-called Hellman's shear exponent.⁸

The association of a turbine's power curve with its associated Rayleigh distribution allows one to estimate a theoretical *AEP* (Annual Energy Production),⁹ which is calculated as

$$AEP = T \cdot \int_{V_{ci}}^{V_{co}} [(f(V) \times P(V))] dV \quad (4.3.7)$$

where $T = 8,760$ is the number of hours per year, $f(V)$ is wind speed's p.d.f., $P(V)$ is the wind turbine power curve (in W) and V_{ci} and V_{co} are resp. cut-in and cut-off wind speeds. The THEWINDPOWER database provided all information about the wind power market. It records some 28,000 wind farms all over the world. We are especially interested in three variables in this file: the geographical location of wind farms, the operating turbine and the height of it. It allows us to:

- First, get the onsite average wind speed at reference height 50m thanks to the GLOBAL WIND ATLAS database (V_i^{ref} , cf Eq. 4.3.6). Then, it is possible to estimate the average wind speed on site i at hub height, V_i ;
- Second, thanks to the THEWINDPOWER database, to retrieve the power curve of the operating turbine, $P_j(V)$. It will also be used to retrieve power curves of the competing turbines that will be identified later.

Given this information, one can (i) fit an hourly wind speed distribution for any site (see Eq. 4.3.4) and, consequently, (ii) compute the expected annual energy production of (any) specific wind turbine model j on the park i 's site, AEP_{ij} . As THEWINDPOWER database provides power curves by 0.5 m.s^{-1} bins, the *AEP* of each wind turbine is estimated using

⁸For onshore installations, α is often considered to take the value $\frac{1}{7}$; see for instance [Peterson and Hennessey \(1978\)](#).

⁹The main hypothesis behind it is a 100% availability of the turbine (i.e. no maintenance).

the same method as in the previous chapter, except that each wind park is associated with its own wind speed distribution.

Due to availability of data, our sample consists in 1,365 wind farms commissioned between 2008 and 2016 in 10 European countries: Austria, Belgium, Denmark, France, Germany, Italy, Netherlands, Portugal, Spain and United-Kingdom. Figure 4.3.1 provides the exact location of those parks.



Figure 4.3.1: Parks included in the sample

Reconstitution of the choice set

Construction of the choice set once again relies on the THEWINDPOWER database. As there is a quite high number of different wind turbine models relative to the number of choice situations, we focus on the choice of a wind turbine manufacturer.¹⁰ The idea is that, when choosing a wind turbine model, the wind park developer “knows what he wants” in terms of turbine characteristics.¹¹ Thus, the choice set is constructed by selecting the closest substitute, among the turbines available *ex ante* from the different manufacturers, to the operating model observed *ex post* and thus actually selected. To find this “closest” model, we use the Canberra distance based on a vector of three characteristics: the annual energy production on site, the rotor size and the rated power. The Canberra distance allows us to

¹⁰First, it is consistent with the idea of estimating learning curves at the firm level. Second, it has the advantage of limiting the number of alternatives in the random profit model.

¹¹Which is consistent with the existence of local consultation during the project development phase.

take into account the scale issue implied by the units of the characteristics (resp. Wh, m, W). Hence, the distance between models j and k is given by:

$$d(\mathbf{j}, \mathbf{k}) = \sum_{i=1}^3 \frac{|j_m - k_m|}{|j_m| + |k_m|} \quad (4.3.8)$$

where j_m is the m^{th} characteristic of model j , $m \in \{1, 2, 3\}$ with $1 = AEP$, $2 = \text{rotor size}$, $3 = \text{rated power}$.

i	j	Closest model	d_j	choice $_i$	AEP_{ij}	D_j	RP_j
1	Enercon	E82/2000	0.106	0	6158.775	82	2000
1	Nordex	N90/2300	0.072	0	6670.242	90	2300
1	Senvion	MM92/2050	0.000	1	6620.439	92	2050
1	Vestas	V90/2000	0.047	0	6318.361	90	2000

Note: d_j is the Canberra distance between model j and the actual operating model (choice $_i = 1$)

Table 4.3.1: Example of a choice situation: Langres Sud wind farm (Haute-Marne, France)

Table 4.3.1 displays the reconstituted choice set faced by Langres Sud wind farm's developer. The wind turbines that equip this park are MM92/2050 turbines from German manufacturer Senvion. The expected Annual Energy Production of one such turbine at the farm's location is 6,620 MWh for a 92 meters blade length and a 2050 MW rated power. Among Enercon's wind turbines available at commissioning year of park i and which height interval includes the chosen model's height,¹² the E82/2000 is the most similar with respect to AEP , rotor size and rated power. It is thus considered as Enercon's competing turbine.

Figures 4.3.2 and 4.A.3 provide information about several characteristics of commissioned wind turbines, by manufacturer. For reasons that will be developed further, Figure 4.3.2 displays information about the evolution in the average characteristics value relative to year 2008. Figure 4.A.3 illustrates average characteristics in absolute terms. We observe that turbines from Enercon are on average smaller than others with respect to rotor size. Eq. 4.3.1 shows that rotor diameter positively affects the power output of turbines. Indeed, the larger the rotor, the more kinetic energy from the wind is captured. More interestingly, we observe that despite their relatively small size, Enercon's turbines perform well with regards to the expected Annual Energy Production. This suggests that these turbines show better performances at converting kinetic energy into electric energy.

¹²One wind turbine can be installed at different height levels. THEWINDPOWER provides information about (i) the height of turbines installed in park i , and (ii) for each wind turbine, the minimum and maximum height.

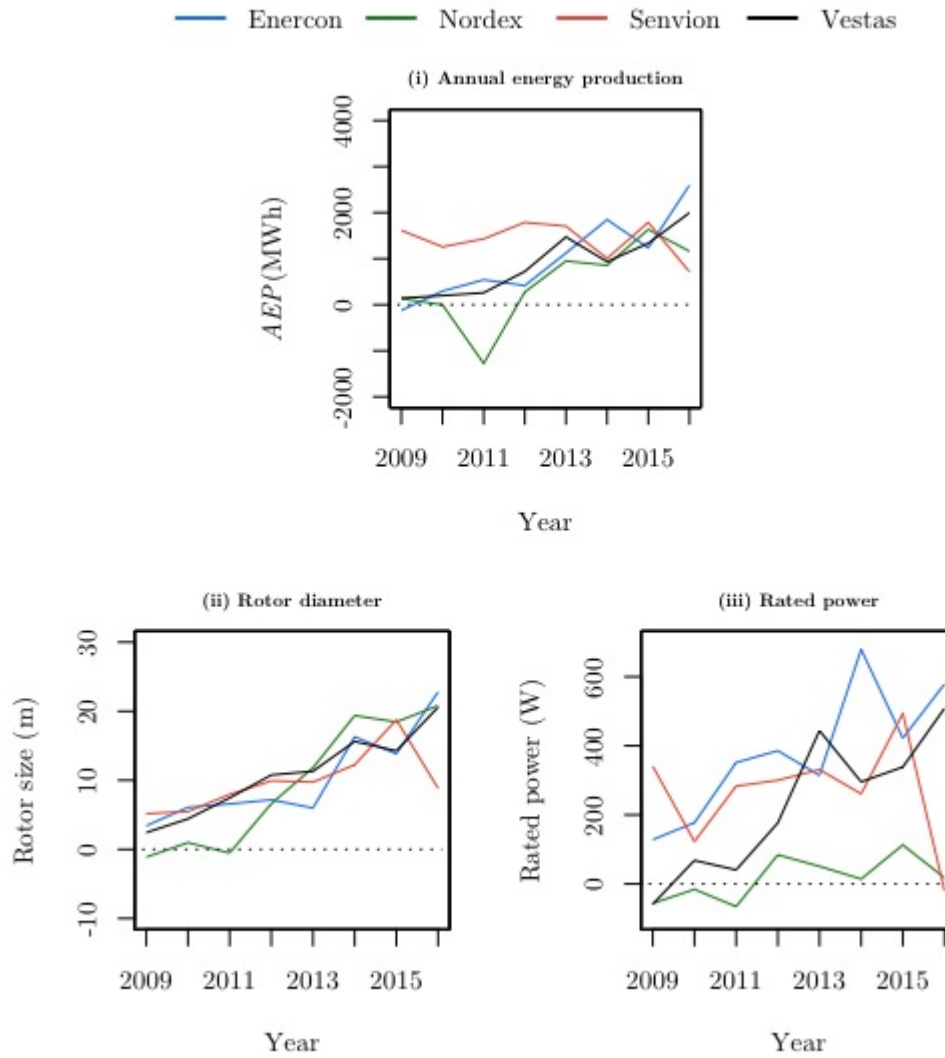


Figure 4.3.2: Differences between manufacturers according to several turbine characteristics, relative to the annual average characteristic computed for commissioned turbines

4.4 Modeling individual choices: the conditional *logit*

Our methodology consists in modeling wind turbine choice based on the traditional random utility model. One major difference is that the relevant choice criteria is the *NPV* described in Section 4.2.

The conditional *logit* model (McFadden, 1974; Train, 1986) considers that individual i (in our case a wind park developer) chooses the alternative j (here, a wind turbine model) that maximizes her utility (here, profit). Several factors may affect this choice: some are observable, some are not. The relationship between those factors and the agent's choice

can be summarized by a function that the literature calls the *behavioral process* and which is generally assumed to be linear with respect to its different components.

In the context of investment decisions, this translates into a $\Pi(\cdot)$ function in which the observed profit $\pi(\cdot)$ is linearly related to the observable characteristics z_{ij} via the β parameters. We also include the ϵ_{ij} error term that represents the unobserved factors. Thus, we have:

$$\Pi_{ij} = \pi(z_{ij}, \beta) + \epsilon_{ij} \quad (4.4.1)$$

Then, we can define the probability ξ_{ij} that park developer i chooses alternative j among the choice set J_i that she faces:

$$\begin{aligned} \xi_{ij} &= Pr(\Pi_{ij} > \Pi_{ik}, \forall k \in J_i \text{ and } k \neq j) \\ \xi_{ij} &= Pr(\pi_{ij} + \epsilon_{ij} > \pi_{ik} + \epsilon_{ik}, \forall k \in J_i \text{ and } k \neq j) \\ \xi_{ij} &= Pr(\epsilon_{ik} - \epsilon_{ij} < \pi_{ik} - \pi_{ij}, \forall k \in J_i \text{ and } k \neq j) \end{aligned} \quad (4.4.2)$$

This is the general form of discrete choice models. The assumption about the distribution of the error term leads to different models. When focusing on the *logit* model, the error term is supposed to be Gumbel distributed, such as its probability density function is as follows:

$$f(\epsilon_{ij}) = e^{-\epsilon_{ij}} e^{-e^{-\epsilon_{ij}}} \quad (4.4.3)$$

Under this assumption, the probability that agent i chooses alternative j is given by:

$$\xi_{ij} = \frac{e^{\pi_{ij}}}{\sum_{k \in J_i} e^{\pi_{ik}}} \quad (4.4.4)$$

One can model the above Equation 4.2.9 by defining a random profit function of the form:

$$\Pi_{ij} = \pi(X_{ij}, \beta) + \epsilon_{ij} \quad (4.4.5)$$

It is considered here that unobservable factors encompass elements that can be improved thanks to the innovation process. Based on a survey of Finnish wind power companies, [Sarja and Halonen \(2013\)](#) identified the main factors that affect the choice by wind park developers of a turbine model. They can be classified into several categories which most important ones are, by decreasing order of importance: (i) reliability, (ii) production volume, (iii) cost factors, and (iv) availability factors. The unobserved factors typically include the cost of the turbine (that represents around 70% of the A_j from Eq. 4.2.9), which we do not directly observe. With regards to it, process innovation has a key role to play since

it is supposed to lower the cost of technology. However, product innovation may as well contribute to improving the unobserved factors: for instance, increasing turbines' lifetime may be reached through the use of new materials. The following is an attempt to assess the importance of process innovation in the choice of wind turbine. Also, note that the choice of a wind turbine manufacturer may be affected by organizational innovation. For example, availability factors in the sense of [Sarja and Halonen \(2013\)](#) include the rapid ability of spare parts.

As innovation is a dynamic process, we wish to appreciate the evolution in the effect of unobservables over time. In this objective, we include a year categorical variable to the model. The value of the associated estimates will provide information about the unobserved elements that condition the preference for a particular wind turbine manufacturer. We also include additional variables. The first one is related to the impact of domesticity in the choice process of wind farm developers highlighted by [Sarja and Halonen \(2013\)](#). The second one is the rated power of the turbine, which is an important turbine characteristic since it defines the installed capacity. Finally, by considering that the observed part of the profit function is linearly related to the predictors, we have the following model:

$$\Pi_{ij} = \beta_1 R_{ij} + \beta_2^j AEP_{ij} + \beta_3 D_j + \beta_4 RP_j + \beta_5 DOM_{ij} + \gamma^j YEAR_i + \epsilon_{ij} \quad (4.4.6)$$

in which $YEAR_i$ is a categorical variable indicating the commissioning year of park i . As the year variable is individual (i.e. park)-specific, they have to be included with differentiated parameters.¹³ This leads to the computation of $(J-1)(N-1)$ estimates, with J the number of alternatives in the choice set and N the number of periods. Interpretation is made relative to the reference category of the year variable (here year 2008). DOM_{ij} is a dummy variable that takes the value 1 if park i is in manufacturer j 's country of origin, 0 otherwise. We allow the parameters associated with the AEP to vary across manufacturers to account for the fact that manufacturers may differ in the O&M cost they propose (see Eq. 4.2.8). Table 4.4.1 provides a summary of the used variables.

4.5 Results and discussion

Table 4.5.1 provides the estimated parameters of the demand model. For the sake of readability, estimates for the year dummies are displayed further.

¹³In the original random utility model, only differences in utility are relevant: in such a fashion, individual-specific explanatory variables drop out from the model.

Name	Description	Unit
R_{ij}	Revenue generated by manufacturer j 's turbine in park i 's location	EUR
D_j	Rotor diameter	m
RP_j	Rated power	W
DOM_{ij}	Domesticity	<i>Dummy</i>
$AE P_{ij}$	Expected Annual Energy Production from manufacturer j 's turbine in park i	Wh
$YEAR_i$	Commissioning year of park i	<i>Categorical</i>

Table 4.4.1: Variables description

<i>Dependent variable:</i>	
Choice	
Revenue	0.075*** (0.0205)
Rated power	−0.422** (0.1967)
Rotor diameter	−0.020* (0.0103)
Domestic	0.810*** (0.1194)
$AE P_{Vestas}$	5.999 (4.903)
$AE P_{Enercon}$	8.179 (4.989)
$AE P_{Nordex}$	−0.131 (5.062)
$AE P_{Senvion}$	−1.002 (4.648)
Observations	1,211
Log Likelihood	−1,473.53
<i>Note:</i> * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$	

Table 4.5.1: Estimation

As all of the variables displayed in Table 4.5.1 are alternative-specific, we can directly interpret the sign of the estimates. What we observe is that almost all of the estimates are significant and have the expected sign. We observe that the probability of choosing a particular manufacturer increases with the expected revenue from commissioning the associated wind turbine. Also, it appears that wind farm developers are more likely to choose a domestic alternative. Both these results are consistent with the qualitative study

conducted by [Sarja and Halonen \(2013\)](#). More interestingly, results suggest that, for a given production volume, park developers are more likely to choose smaller machines. This might be a consequence of the square-cube law of wind power, that states that the cost of a turbine grows faster with size than energy output does. In the same vein, we observe that turbines' rated power has a negative impact on developers' choices, all other characteristics being equal. Finally, the coefficients associated with the expected *AEP*, that encompass manufacturers' own unit O&M cost, do not appear as significant.

It is worthwhile to notice that the model performs pretty well at predicting the overall market shares of manufacturers.¹⁴ Table 4.5.2 displays both predicted and actual market shares. It constitutes a positive signal about including years dummies to capture the effect of unobservables on the choice of a WT manufacturer.

	Enercon	Nordex	Senvion	Vestas
Actual market share	31.46%	9.17%	21.22%	38.15%
Predicted market share	30.71%	9.26%	22.47%	37.56%

Table 4.5.2: Actual and predicted market shares

As the qualitative year variable is individual (i.e. park)-specific, the sign of the related estimates can not be directly interpreted. Figure 4.5.1 instead displays the average marginal effects (AMEs) associated with the year variable. It has to be interpreted relative to the reference year, i.e. 2008. For instance, a discrete variation in the year variable from 2008 to 2009 leads to an increase in the probability of choosing a Vestas' turbine by around 9 percentage points. Thus, one can appreciate the attractiveness of manufacturers over time.

The marginal effects encompass the effects of time on the probability of selecting one particular WT manufacturer. We observe that the dynamics of the marginal effects follows a very similar path compared to the observed yearly market share in the sample, highlighted in Figure 4.5.2. For the sake of comparison, market shares are expressed relative to those of year 2008, but graphs for market share, technical characteristics and patents in absolute terms are displayed in Appendix 4.A. However, the ranking of manufacturers with respect to the marginal effects is not the same than the ranking with respect to their annual market shares. For instance, we observe that at the beginning of the period, marginal effects associated with Senvion exceed those of Vestas while, at the same time, the latter shows a higher market share. This may be explained by differences in the characteristics of turbines. One can notice from Figure 4.3.2 that, over the same period, the relative average *AEP* of

¹⁴In each choice situation, the expected “winner” is the manufacturer that has the higher probability of being chosen.

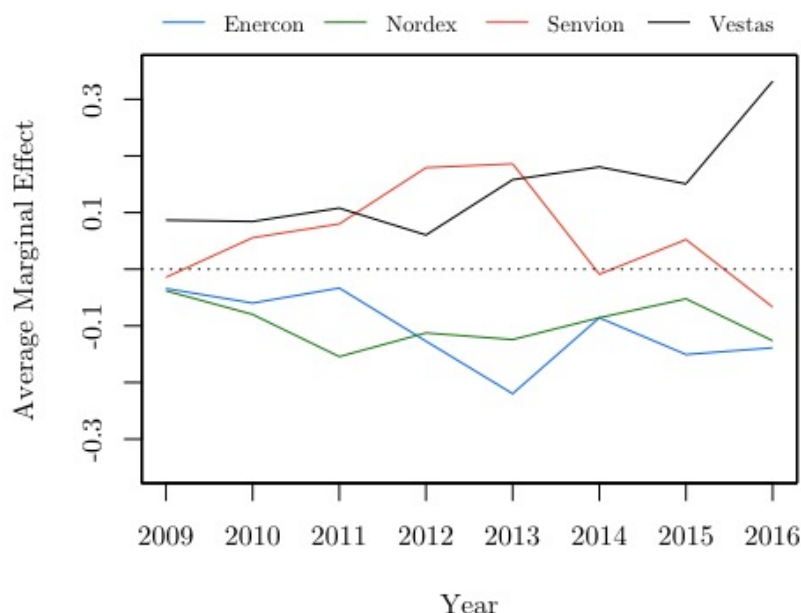


Figure 4.5.1: Marginal effects for the year dummies (relative to year 2008)

Senvion’s turbines is higher than those of other manufacturers. Indeed, recall that *AEP* conditions the expected revenue to be earned by wind farm developers, and that expected revenue has been found as a major turbine selection criterion. In the same vein, the relative market share of Enercon between 2012 and 2016 is lower than Nordex’ one. However, as evidenced by the AMEs, both firms seem to perform quite the same with regards to the unobserved factors, suggesting that Nordex performs better with regards to observable technical characteristics. Indeed, focusing on Figure 4.3.2 leads one to conclude that the relative average value for rated power, which is negatively valued by wind park developers, is lower when it comes to Nordex than to other manufacturers.

It is of interest to assess whether the direction of innovation towards process innovation could explain the differences between manufacturers with respect to the unobservable part of the profit expected by their customers. In the following, we will use patent counts in this purpose. Patents were retrieved from the PATSTAT database of the European Patent Office and belong to Y02E 10/7 class and sub-classes of the Cooperative Patent Classification (“Wind energy”). The graphs from Figure 4.5.3 display two information: (i) the average “processness” of newly filed patents, and (ii) the average “processness” of patent portfolios. The processness measure is the one introduced and extensively discussed in Chapter 2 and aims at quantifying the extent to which a patent is process-oriented. Based on a keyword search in patent descriptions, the “processness” of a patent is computed as the ratio between the number of process-related keywords and the total number of keywords

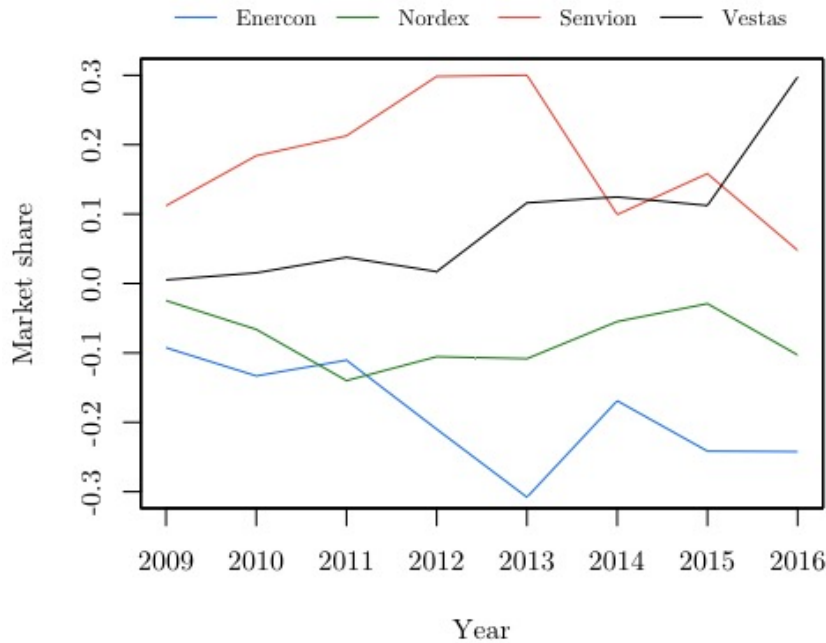


Figure 4.5.2: Evolution in the observed market shares (relative to year 2008)

(product and process keywords).¹⁵ Thus, a processness value greater than 0.5 indicate that the underlying patent is more process-oriented than product-oriented. Patent “productness” can straightforwardly be calculated in the reverse way. In part (i) of Figure 4.5.3, granted patents are patents filed at the EPO at a given year that have been granted afterwards. A patent portfolio (part (ii) in Figure 4.5.3) accounts for patent renewals since it includes all (granted) patents that are active at a given year t , i.e. filed before year t and lapsed, if so, after year t . Once again, both patent counts are provided relative to the 2008 reference year.

The growing attractiveness of Senvion at the beginning of the period coincides with kind of a reorientation of the firm’s inventive efforts towards process innovation. Indeed, the average processness of Senvion’s patent portfolio has experienced a brutal rise between 2008 and 2009 and has not stopped increasing until 2016 at least. But this phenomenon does not hold over the whole period since the AMEs curve drops at year 2012 and then keeps decreasing while the processness of Senvion’s portfolio remains shifting upwards. When focusing on Vestas, we observe that the curves associated with the processness of successfully filed patents and the AMEs follow a very similar pattern. However, this result could not be generalized to other manufacturers. Indeed, there does not seem to be a

¹⁵The keywords used in this process have been proposed by Banholzer et al. (2019).

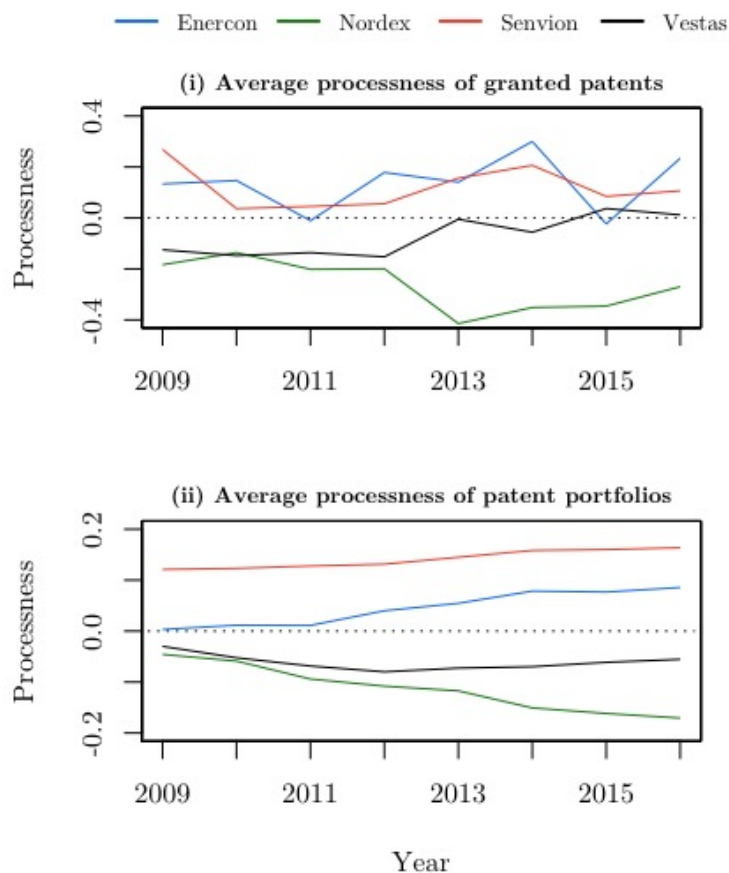


Figure 4.5.3: Evolution in the relative average "processness" of patents and patent portfolios

correlation between the average "processness" of patents and the AMEs on the probability of choosing one particular WT manufacturer.

Figure 4.5.4 accounts for the global number of process patent in the sector. As both market shares and AMEs lie into the $[0, 1]$ interval, it makes few sense to compare these measures with absolute patent counts. Instead, we computed for each manufacturers the share of the process patent portfolio in the whole process patent portfolio (i.e. process patents portfolios of the four manufacturers put together). Still in order to compare the dynamics, the shares are expressed relative to year 2008 and displayed in Figure 4.5.4. For instance, the value of the relative share of process portfolios for Senvion in year 2011 is near 0.05. In means that, relative to 2008, the share of Senvion's process portfolio in the global process portfolio has increased by 5 percentage points.

Focusing on the evolution in the weights of manufacturers in the global process portfolio provides useful insights. Indeed, it is interesting to observe that Senvion and Vestas, that have positive AME values over almost the whole period, also have their share in the global process portfolio increasing over the period. Reversely, firms having negative AME values

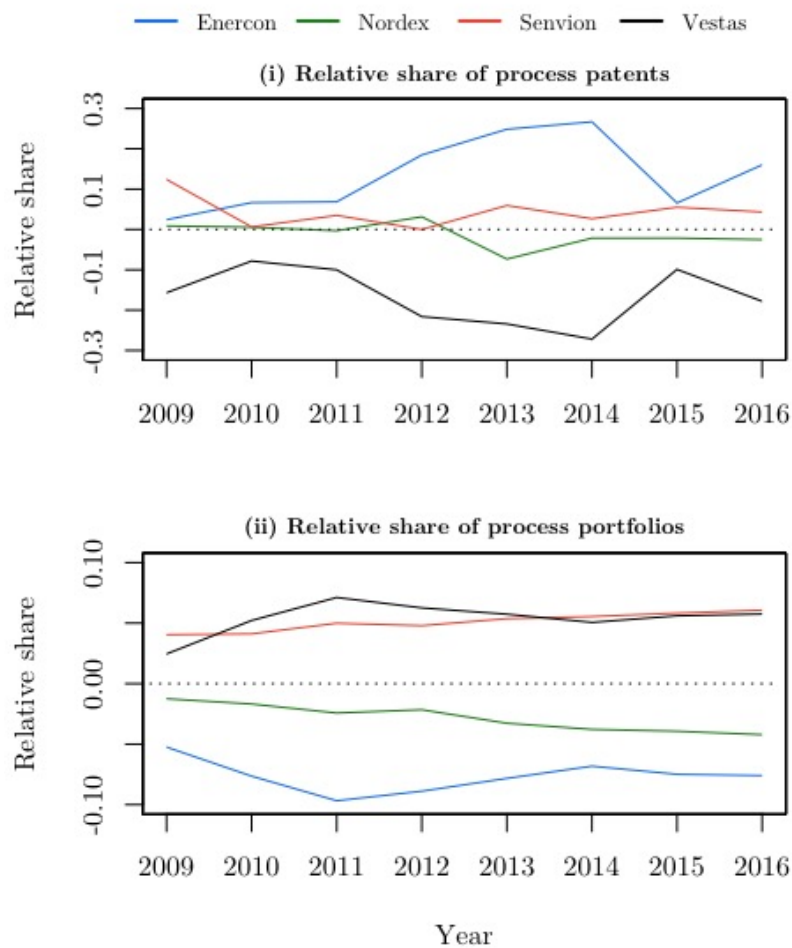


Figure 4.5.4: Evolution in relative global patent filing and portfolio size

are those whose share of process portfolio decreases over time. This would suggest that, to some extent, process innovation efforts from firms are rewarded with higher market shares. Finally, Figure 4.5.5 displays information about firms' experience on the basis of the cumulative installed capacity prior to a given year. In the same vein, it is the share of this sum relative to the total installed capacity and relative to year 2008. If experience is directly related to the observed market share, some variance exist since (i) in our model, we have implicitly considered that each wind park developer purchased one turbine, and (ii) the cumulative installed capacity accounts for all turbines commissioned prior to 2008. We might observe that Senvion's representation in total installed capacities is increasing at a quite constant rate relative to year 2008. This could be an explanation for the relative rise in the effect of unobservables on the choice of a WT manufacturer. However, evolution of both Enercon and Vestas contradicts this. Finally, process innovation seems to be a better candidate to explain the selection of a wind turbine supplier than experience.

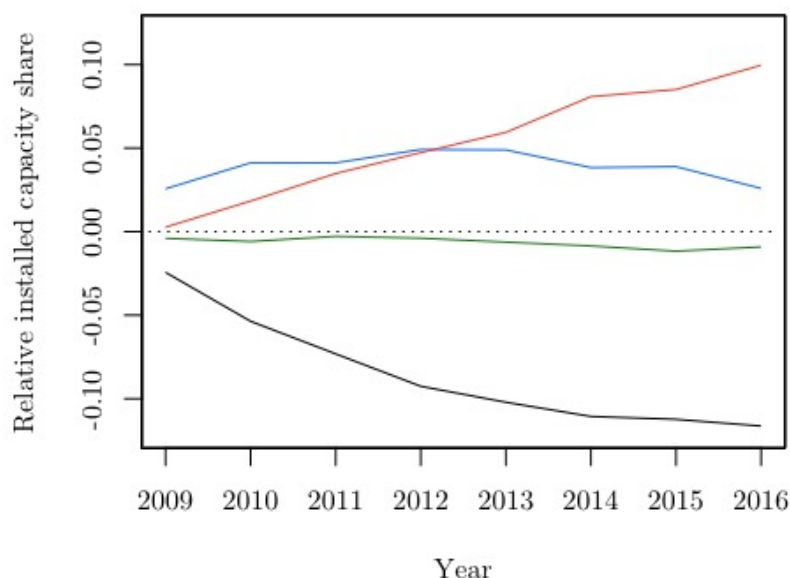


Figure 4.5.5: Evolution in relative experience

4.6 Conclusion

This paper provided an attempt to assess whether wind turbine manufacturers involved in the process innovation process are more likely to be chosen to equip wind farms. The rationale is that, once the effects of technical characteristics are neutralized, the impact of the unobserved factors on the probability of selecting one manufacturer rather than another might reflect differences in the cost of technologies. The results from the qualitative study conducted by [Sarja and Halonen \(2013\)](#) highlighted the fact that cost factors, along with unobserved factors such as reliability or availability, play an important role in wind turbine selection.

Using data on European wind farms, we set up a conditional *logit* model for the choice of a wind turbine manufacturer. Our result highlight the positive and significant effects of production volume (through revenue) and domesticity in this process, consistently with [Sarja and Halonen \(2013\)](#). Another finding is that, all other characteristics being equal, the rotor size has a significant negative impact on the probability for a turbine to be chosen. This is consistent with the *square-cube law of wind power* that states that wind turbine cost increases faster with size than energy output does, due to the required quantities of raw materials. To the best of our knowledge, this practitioner rule-of-thumb had not been tested yet.

We then considered whether the effect of time on the probability for a particular WT manufacturer to be chosen could be the result of increased process innovation efforts from

firms. Based on patent counts, our results suggest that, at constant technical characteristics, firms involved in process innovation are being chosen to a greater extent. This result, still having to be interpreted with caution, might be insightful with regards to the importance of the patent system in protecting and fostering process innovation and the use of (process) patent counts to reflect this very same process.

This study suffers a certain number of limitations. Especially, due to data constraints, we had to drop out some quite important manufacturers from the choice set. Subsequently, extending the choice set and/or the time period could be useful to conduct a proper panel data analysis. Those limitations could be overcome in future research.

Appendices of Chapter 4

Appendix 4.A Graphs in absolute values

4.A.1 Market share

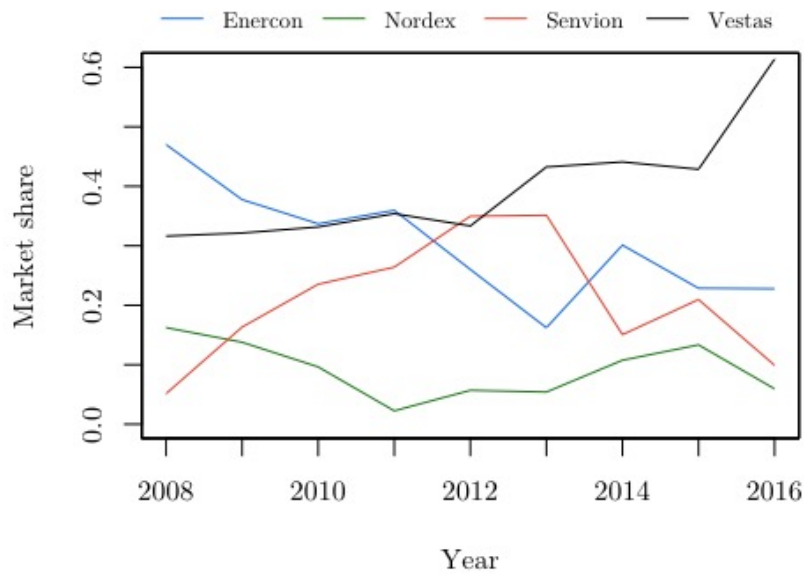


Figure 4.A.1: Evolution in the market shares of firms

4.A.2 Average processness

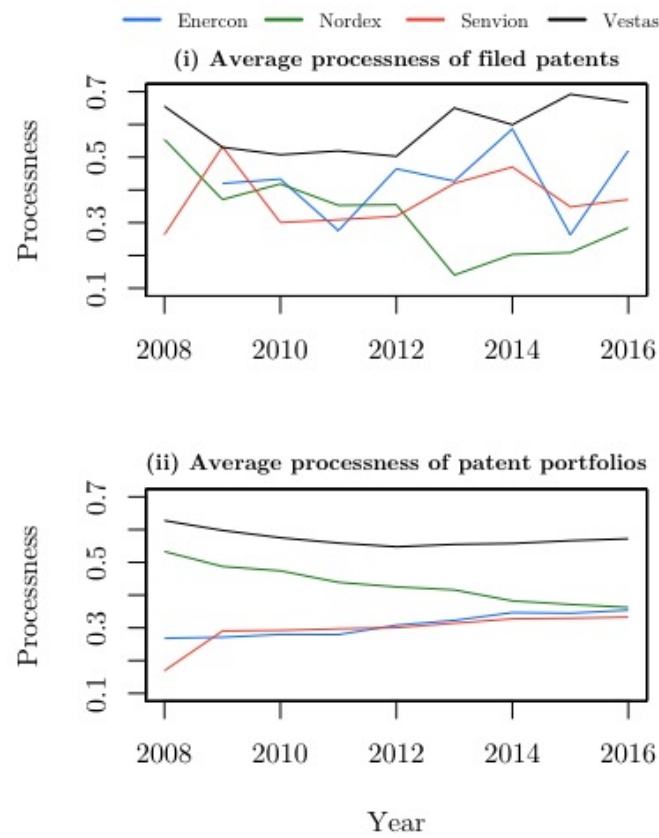


Figure 4.A.2: Evolution in the “processness” of patents and patent portfolios, by firm

4.A.3 Characteristics of commissioned turbines

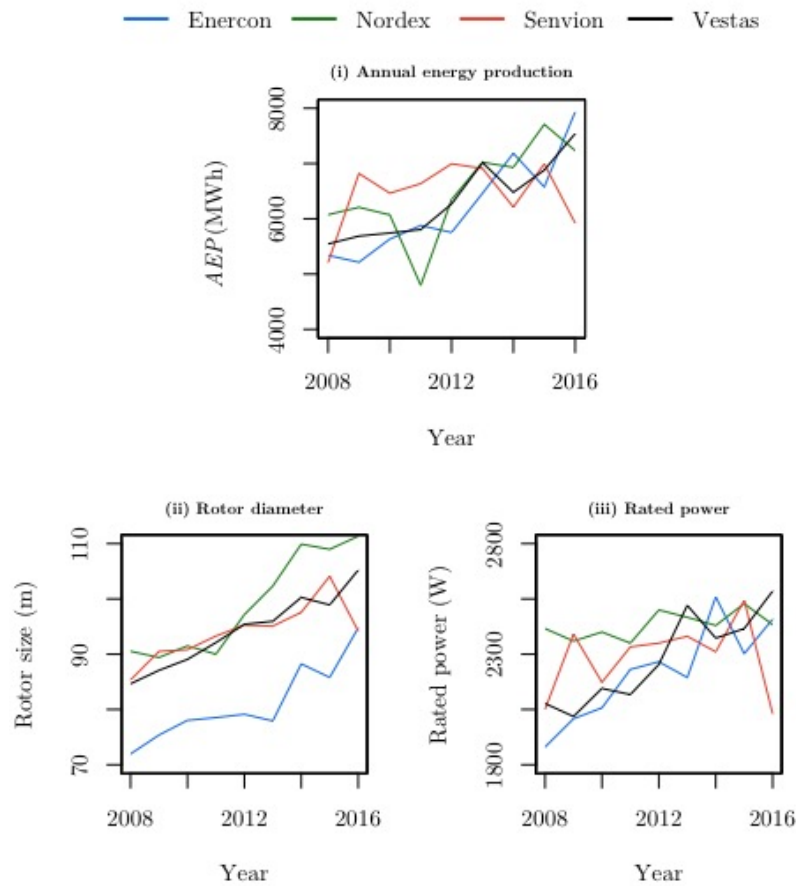


Figure 4.A.3: Evolution in the characteristics of installed turbines

* * *

Concluding remarks

THE present Ph.D dissertation has been interested in the economics of the patent system. Such a system is supposed to provide a response to knowledge externalities. Especially, since the non-rival nature of knowledge makes it reproducible at almost no cost by competitors, private agents lack incentive to invest in research. Patents thus aim at encouraging firms to get involved in the innovation process – and, ultimately, to spur technical change – by rewarding them with a temporary right-to-exclude third parties from any use of the underlying invention. This translates in economic terms into a socially harmful market power and leaves space for strategic behaviors since it creates opportunities for firms to secure technological positions by hampering technology development by competitors. The inherent social cost of the patent system, associated with the possibility for firms to behave strategically, calls for a careful analysis of the relationship between patents and technical change. It is all the more justified by the fact that patent information is precisely widely relied on to reflect technical change. Indeed, innovation lacks generic ready-to-use proxies. Patents constitute a plentiful source of information, which is a consequence of the fact that patent protection is conditional upon the divulgation and publication of the underlying invention's content.

When it comes to green innovation, things get even more complex. Indeed, the environmental externality implies that private agents poorly account for environmental damages in their investment decisions. Yet, current and future states of climate change make the orientation of R&D activities towards environment-friendly technologies a critical issue and, beyond promoting innovation, policy makers have to promote low-carbon innovation. In this objective, they need to correct for both knowledge and environment related externalities, which is usually referred to as the *double externality problem*. The economic literature about this issue has pointed out the need to complement environmental policy instruments (such as feed-in tariffs or CO₂ pricing) with a dedicated support to green technologies. At the time being, probably the best example of such support has been the fifth cluster of the Horizon Europe programme from the European Commission, through which green innovation projects are selected for funding. To a lesser extent, patents have been mobilized

in this objective as well. The fast-tracking of green patent applications experimented in a dozen of countries worldwide is supposed to lower the cost of protection for green inventions relative to brown ones. However, the patent system does not appear as the main lever to act on, even though results from this thesis tend to give credit to the idea of a green patent policy.

Based on an extensive analysis of the wind power industry, results from this research support the use of patents to drive the shift of inventive activity towards green technologies as well as their use as an indicator of this switch. Indeed, after excluding the existence of strategic patenting in the first chapter, the remainder of the dissertation highlights a positive relationship between patent counts and contributions to technical change, with regards to both product and process innovation.

Chapter 1 proposes a study of patent oppositions between firms in the wind industry. It is emphasized that patent oppositions can reflect strategic behaviors of firms since it allows competitors to challenge the validity of a patent. Especially, regardless of the final decision by the office with respect to the case, re-examination delays and the uncertainty it creates may reward opponents with an advantage. Also, it is considered that firms may rely on defensive blocking strategies by building a patent wall around one key invention. Securing technological positions in such a manner can ultimately restrict the development and improvement of valuable innovations. An analysis of the determinants of patent oppositions and their outcomes using both patent and firm information leads us to conclude that neither strategic oppositions nor blocking strategies are common practice in the wind industry. Contributions of this chapter include an original modelling of opposition outcomes, that fully takes advantage of information on the legal status of patents, as well as proxying blocking strategies on the basis of objective data.

In Chapter 2, we developed a methodology to distinguish patents protecting product and/or process inventions based on text-mining techniques. Furthermore, we considered the fact that one single invention can be both product and process and computed the “productness” and “processness” of patents, i.e. the product and process share of patents, respectively. A descriptive analysis suggests that, while product innovation is dominant over the 1990-2017 period in the wind power industry, process innovation is gradually gaining ground since the 2004-2005 period. We suggest that promoting wind power *via* feed-in tariffs or CO₂ pricing can have a differentiated impact. Notably, feed-in tariffs should promote process innovation due to the fact that revenue from wind parks is less sensitive to demand. In such a context, decreasing the cost of technology appears as more worthwhile than improving the electricity output of turbines. Reversely, carbon pricing should promote product innovation.

The decrease in the carbon price following the 2008 subprime crisis is in line with this hypothesis.

Confronting patent data with objective measures of technical change has been the objective of Chapter 3. More precisely, we have aimed at appreciating the relationship between patent counts and contributions to technical change at the firm level. To do so, we focus on a measure of product innovation, i.e. the evolution in the technical characteristics of wind turbines. It is worth noting here that to increase the energy production from their machines, wind turbine manufacturers can both increase the rotor size to capture more kinetic energy from the wind and/or improve the power coefficient that reflect the efficiency in the conversion of kinetic energy into electric energy. Based on these two characteristics, we constructed the technology frontier over time. We thus are able to capture the contribution of one particular turbine entering the market at a given year by comparing its location relative to the frontier. A turbine is considered as innovative if it contributes to push the frontier forward, and radial distance is used to compute the extent of this contribution. Using panel data analysis, we show that firms having contributions to technical change are mostly those holding patents. However, we observe that (i) before the mid-2000s, little patenting activity has not been a hurdle to technical change, and (ii) very large firms, despite applying and being granted many patents, are not especially innovative with regards to our measure. Finally, if we observe a positive correlation between patent counts and contributions to technical change, we emphasize the need to account for the time-to-market of innovations and to consider portfolios of renewed patents instead of simple patent counts.

In a very similar vein, Chapter 4 is an attempt to assess whether patent counts are good proxies for process innovation. In the context of wind power, process innovation should translate into a decrease in the price charged by wind turbine manufacturers to lower the investment cost of commissioning wind parks. Based on observations about more than a thousand wind farms – and actual wind turbines that equip them –, we set a discrete choice model in which wind park developers are to choose one wind turbine manufacturer. Determinants of this choice include the expected revenue from commissioning one specific turbine in wind park location as well as technical characteristics of turbines. Unobservables include the price of wind turbines, but also unobserved factors such as reliability. We observe a co-evolution between the impact of unobserved factors on the choice of a manufacturer and the latter's process patent portfolio size, which suggests that patent counts reflect process innovation activity by companies.

Put together, these elements are a positive signal with respect to the European patent system. Indeed, the fact that strategies that might hamper technology development are not

a widespread practice suggests that firms do not take advantage of the patent system to extract undue rents. This is in line with results from the third chapter according to which, when time-to-market of innovations is accounted for, patent portfolio size are positively correlated with objective measures of product innovation at the firm level. In a similar way, the last chapter shows that, when accounting for technical characteristics of goods, firms undertaking process innovation efforts – as evidenced by patent information – are more likely to be chosen by purchasers. As such, there is no evidence that the patent system fails at promoting innovation. Consequently, it seems that patent information provides useful insights with regards to the innovation process and can be safely used to reflect the extent and direction of technical change.

Although these results hold for a particular (*green*) sector, namely wind power, they provide support to the idea of switching from the *one-size-fits-all* principle towards a dedicated patent policy for green innovation. This would be consistent with the special treatment of “green” inventions, that are recorded in a dedicated transversal class since the implementation of the Cooperative Patent Classification. To the best of our knowledge, only a few authors have considered reshaping the patent system in the objective of inducing green innovation, and no consensus has been found with respect to the optimal design of such a green patent policy. Especially, the latter appears to depend on the existence and stringency of the environmental policy. Results from this thesis call for further research about the joint design of environmental and patent policies to foster the development of clean technologies.

* * *

Bibliography

- Abrams, D. S., U. Akcigit, and J. Grennan (2013). Patent value and citations: Creative destruction or strategic disruption? Working Paper 19647, National Bureau of Economic Research.
- Acemoglu, D., P. Aghion, L. Bursztyn, and D. Hemous (2012). The environment and directed technical change. *The American Economic Review* 102(1), 131–66.
- Arrow, K. (1962). Economic welfare and the allocation of resources for invention. In *The rate and direction of inventive activity: Economic and social factors*, pp. 609–626. Princeton University Press.
- Arundel, A. (2001). The relative effectiveness of patents and secrecy for appropriation. *Research Policy* 30(4), 611–624.
- Banholzer, N., V. Behrens, S. Feuerriegel, S. Heinrich, C. Rammer, U. Schmoch, F. Seliger, and M. Wörter (2019). Knowledge spillovers from product and process inventions in patents and their impact on firm performance. Research report, ZEW-Gutachten und Forschungsberichte, ETH Zurich, KOF Swiss Economic Institute, Zurich.
- Banker, R. D., A. Charnes, and W. W. Cooper (1984). Some models for estimating technical and scale inefficiencies in data envelopment analysis. *Management Science* 30(9), 1078–1092.
- Baudry, M. and C. Bonnet (2019). Demand-pull instruments and the development of wind power in Europe: A counterfactual analysis. *Environmental and Resource Economics* 73(2), 385–429.
- Baudry, M. and B. Dumont (2016). Market maturity, patent renewals and the pace of innovation: The case of wind power in Germany. *Journal of Innovation Economics and Management* 20(2), 131–150.
- Baudry, M. and B. Dumont (2017). *Patents: Prompting or restricting innovation?* John Wiley & Sons.
- Baum, C. F. (2008). Modeling proportions. *The Stata Journal* 8(2), 299–303.
- Bessen, J. and E. Maskin (2009). Sequential innovation, patents, and imitation. *The RAND Journal of Economics* 40(4), 611–635.

- Blind, K., K. Cremers, and E. Mueller (2009). The influence of strategic patenting on companies' patent portfolios. *Research Policy* 38(2), 428–436.
- Blind, K., J. Edler, R. Frietsch, and U. Schmoch (2006). Motives to patent: Empirical evidence from Germany. *Research Policy* 35(5), 655–672.
- Blundell, R., R. Griffith, and J. Van Reenen (1999). Market share, market value and innovation in a panel of British manufacturing firms. *The Review of Economic Studies* 66(3), 529–554.
- Boer, H. and W. E. During (2001). Innovation, what innovation? A comparison between product, process and organisational innovation. *International Journal of Technology Management* 22(1-3), 83–107.
- Böhringer, C., A. Cuntz, D. Harhoff, and E. Asane-Otoo (2017). The impact of the German feed-in tariff scheme on innovation: Evidence based on patent filings in renewable energy technologies. *Energy Economics* 67, 545–553.
- Boldrin, M., J. C. Allamand, D. K. Levine, and C. Ornaghi (2011). Competition and innovation. *Cato Papers on Public Policy* 1, 109.
- Boldrin, M. and D. K. Levine (2008). *Against Intellectual Monopoly*, Volume 9. Cambridge University Press.
- Boldrin, M. and D. K. Levine (2013). The case against patents. *Journal of Economic Perspectives* 27(1), 3–22.
- Bonnet, C. (2016). Revisiting the optimal patent policy tradeoff for environmental technologies. Working Paper 2016-34, EconomiX, University of Paris Nanterre.
- Braun, F. G., J. Schmidt-Ehmcke, and P. Zloczynski (2010). Innovative activity in wind and solar technology: Empirical evidence on knowledge spillovers using patent data. Discussion Paper 993, DIW Berlin.
- Burke, P. F. and M. Reitzig (2007). Measuring patent assessment quality — Analyzing the degree and kind of (in)consistency in patent offices' decision making. *Research Policy* 36(9), 1404–1430.
- Calderini, M. and G. Scellato (2004). Intellectual property rights as strategic assets: The case of European patent opposition in the telecommunication industry. Working Paper 158, KITEs, Centre for Knowledge, Internationalization and Technology Studies, Università Bocconi, Milano.
- Cameron, A. C. and P. K. Trivedi (1990). Regression-based tests for overdispersion in the Poisson model. *Journal of Econometrics* 46(3), 347–364.
- Caviggioli, F., G. Scellato, and E. Ughetto (2013). International patent disputes: Evidence from oppositions at the European Patent Office. *Research Policy* 42(9), 1634–1646.

- Charnes, A., W. W. Cooper, and E. Rhodes (1978). Measuring the efficiency of decision making units. *European Journal of Operational Research* 2(6), 429–444.
- Choi, P. S., E. Diaz-Fariña, A. Espinola-Arredondo, and F. Munoz-Garcia (2022). Optimal patent lengths in polluting industries. Working Paper 2022-2, School of Economic Sciences, Washington State University.
- Cincera, M. (2011). Déterminants des oppositions de brevets. *Revue Economique* 62(1), 87–99.
- Cohen, W. M. and S. Klepper (1996a). Firm size and the nature of innovation within industries: The case of process and product R&D. *The Review of Economics and Statistics* 78(2), 232–243.
- Cohen, W. M. and S. Klepper (1996b). A reprise of size and R&D. *The Economic Journal* 106(437), 925–951.
- Cohen, W. M. and D. A. Levinthal (1989). Innovation and learning: The two faces of R&D. *The Economic Journal* 99(397), 569–596.
- Cohen, W. M., R. R. Nelson, and J. P. Walsh (2000). Protecting their intellectual assets: Appropriability conditions and why us manufacturing firms patent (or not). Working Paper 7552, National Bureau of Economic Research.
- Cribari-Neto, F. and A. Zeileis (2010). Beta regression in R. *Journal of Statistical Software* 34(2), 1–24.
- Dechezleprêtre, A. (2013). Fast-tracking “green” patent applications: An empirical analysis. Discussion Paper 1197, Center for Economic Performance, London School of Economics and Political Science.
- Denicolo, V. (1996). Patent races and optimal patent breadth and length. *The Journal of Industrial Economics* 44(3), 249–265.
- Deprins, D., L. Simar, and H. Tulkens (2006). Measuring labor-efficiency in post offices. In *Public goods, environmental externalities and fiscal competition*, pp. 285–309. Springer.
- Dubarić, E., D. Giannoccaro, R. Bengtsson, and T. Ackermann (2011). Patent data as indicators of wind power technology development. *World Patent Information* 33(2), 144–149.
- Ek, K. and P. Söderholm (2010). Technology learning in the presence of public R&D: The case of European wind power. *Ecological Economics* 69(12), 2356–2362.
- Ferrari, S. and F. Cribari-Neto (2004). Beta regression for modelling rates and proportions. *Journal of Applied Statistics* 31(7), 799–815.

- Fischer, C. and R. G. Newell (2008). Environmental and technology policies for climate mitigation. *Journal of Environmental Economics and Management* 55(2), 142–162.
- Freiwald, D. (2013). The Wright lawsuit. *Journal of Aviation/Aerospace Education & Research* 23(1), 9–12.
- Fritsch, M. and M. Meschede (2001). Product innovation, process innovation, and size. *Review of Industrial Organization* 19(3), 335–350.
- Gaessler, F., D. Harhoff, and S. Sorg (2019). Bargaining failure and freedom to operate: Re-evaluating the effect of patents on cumulative innovation. Research Paper 19-11, Max Planck Institute for Innovation & Competition Research Paper.
- Galasso, A. and M. Schankerman (2015). Patents and cumulative innovation: Causal evidence from the courts. *The Quarterly Journal of Economics* 130(1), 317–369.
- Gallini, N. T. (1992). Patent policy and costly imitation. *The RAND Journal of Economics* 23(1), 52–63.
- Gerlagh, R., S. Kverndokk, and K. E. Rosendahl (2014). The optimal time path of clean energy R&D policy when patents have finite lifetime. *Journal of Environmental Economics and Management* 67(1), 2–19.
- Gilbert, R. J. and D. M. Newbery (1982). Preemptive patenting and the persistence of monopoly. *The American Economic Review* 72(3), 514–526.
- Godin, B. and J. P. Lane (2013). Pushes and pulls: Hi(S)tory of the demand pull model of innovation. *Science, Technology, & Human Values* 38(5), 621–654.
- Grafström, J. (2018). International knowledge spillovers in the wind power industry: Evidence from the European Union. *Economics of Innovation and New Technology* 27(3), 205–224.
- Grafström, J. and Å. Lindman (2017). Invention, innovation and diffusion in the European wind power sector. *Technological Forecasting and Social Change* 114, 179–191.
- Graham, S. J. and D. Harhoff (2014). Separating patent wheat from chaff: Would the us benefit from adopting patent post-grant review? *Research Policy* 43(9), 1649–1659.
- Graham, S. J. H., B. H. Hall, D. Harhoff, and D. C. Mowery (2002). Post-issue patent “quality control”: A comparative study of US patent re-examinations and European patent oppositions. Working Paper 8807, National Bureau of Economic Research.
- Greene, W. H. (2011). *Econometric Analysis, 7th Edition* (7th Edition ed.). Prentice Hall.
- Griliches, Z. (1990). Patent statistics as economic indicators: A survey. *Journal of Economic Literature* 28(4), 1661–1707.

- Guellec, D. and B. Van Pottelsberghe (2007). *The economics of the European patent system: IP policy for innovation and competition*. Oxford University Press.
- Hall, B. H. and C. Helmers (2010). The role of patent protection in (clean/green) technology transfer. *Santa Clara High Technology Law Journal* 26(4), 487–532.
- Hall, B. H., A. B. Jaffe, and M. Trajtenberg (2005). Market value and patent citations. *The RAND Journal of Economics* 36(1), 16–38.
- Harhoff, D., B. H. Hall, G. von Graevenitz, K. Hoisl, and S. Wagner (2007). The strategic use of patents and its implications for enterprise and competition policies. Report ENTR/05/82 for DG Enterprise, European Commission.
- Harhoff, D. and M. Reitzig (2004). Determinants of opposition against EPO patent grants — The case of biotechnology and pharmaceuticals. *International Journal of Industrial Organization* 22(4), 443–480.
- Harhoff, D., F. M. Scherer, and K. Vopel (2003). Citations, family size, opposition and the value of patent rights. *Research Policy* 32(8), 1343–1363.
- Harhoff, D., G. von Graevenitz, and S. Wagner (2016). Conflict resolution, public goods, and patent thickets. *Management Science* 62(3), 704–721.
- Haščič, I. and N. Johnstone (2011). CDM and international technology transfer: Empirical evidence on wind power. *Climate Policy* 11(6), 1303–1314.
- Hau, E. (2013). *Wind turbines: Fundamentals, technologies, application, economics*. Springer Science & Business Media.
- Heller, M. A. and R. S. Eisenberg (1998). Can patents deter innovation? The anticommons in biomedical research. *Science* 280(5364), 698–701.
- Hirth, L. and F. Ueckerdt (2013). Redistribution effects of energy and climate policy: The electricity market. *Energy Policy* 62, 934–947.
- Huenteler, J., J. Ossenbrink, T. S. Schmidt, and V. H. Hoffmann (2016). How a product’s design hierarchy shapes the evolution of technological knowledge — Evidence from patent-citation networks in wind power. *Research Policy* 45(6), 1195–1217.
- IEA (2021). Patents and the energy transition: Global trends in clean energy technology innovation. Report, International Energy Agency, joint with the European Patent Office.
- IRENA (2013). Intellectual property rights: The role of patents in renewable energy technology innovation. Report, International Renewable Energy Agency.
- Jaffe, A. B. (1986). Technological opportunity and spillovers of R&D: Evidence from firms’ patents, profits, and market value. *The American Economic Review* 76(5), 984–1001.

- Jaffe, A. B., R. G. Newell, and R. N. Stavins (2005). A tale of two market failures: Technology and environmental policy. *Ecological economics* 54(2-3), 164–174.
- Jaffe, A. B., M. Trajtenberg, and M. S. Fogarty (2000). Knowledge spillovers and patent citations: Evidence from a survey of inventors. *The American Economic Review* 90(2), 215–218.
- Jamieson, P. (2018). *Innovation in wind turbine design*. John Wiley & Sons.
- Johnstone, N., I. Haščič, and D. Popp (2010). Renewable energy policies and technological innovation: Evidence based on patent counts. *Environmental and Resource Economics* 45(1), 133–155.
- Kanwar, S. and R. Evenson (2003). Does intellectual property protection spur technological change? *Oxford Economic Papers* 55(2), 235–264.
- Kapoor, R., M. Karvonen, and T. Kässi (2012). Patent portfolio efficiency using data envelopment analysis: Case of wind power market. In *2012 IEEE International Conference on Industrial Engineering and Engineering Management*, pp. 1122–1126. IEEE.
- Kapoor, R., M. Karvonen, A. Mohan, and T. Kässi (2016). Patent citations as determinants of grant and opposition: case of European wind power industry. *Technology Analysis & Strategic Management* 28(8), 950–964.
- Klemperer, P. (1990). How broad should the scope of patent protection be? *The RAND Journal of Economics* 21(1), 113–130.
- Lambert, D. (1992). Zero-Inflated Poisson regression, with an application to defects in manufacturing. *Technometrics* 34(1), 1–14.
- Lampe, R. and P. Moser (2010). Do patent pools encourage innovation? Evidence from the nineteenth-century sewing machine industry. *The Journal of Economic History* 70(4), 898–920.
- Langinier, C. and A. Ray Chaudhuri (2019). Green technology and patents in the presence of green consumers. *Journal of the Association of Environmental and Resource Economists* 7(1), 73–101.
- Lanjouw, J. O. and M. Schankerman (2001). Characteristics of patent litigation: A window on competition. *RAND Journal of Economics* 32(1), 129–151.
- Lemley, M. A. and C. Shapiro (2005). Probabilistic patents. *Journal of Economic Perspectives* 19(2), 75–98.
- Levin, J. and R. C. Levin (2002). Patent oppositions. Working Paper 283, John M. Olin Center for Studies in Law, Economics and Public Policy.

- Lin, B. and Y. Chen (2019). Impacts of policies on innovation in wind power technologies in China. *Applied Energy* 247, 682–691.
- Lindman, Å. and P. Söderholm (2012). Wind power learning rates: A conceptual review and meta-analysis. *Energy Economics* 34(3), 754–761.
- Lindman, Å. and P. Söderholm (2016). Wind energy and green economy in Europe: Measuring policy-induced innovation using patent data. *Applied Energy* 179, 1351–1359.
- Machlup, F. (1958). An economic review of the patent system. Study 15, Subcommittee on Patents, Trademarks, and Copyrights of the Committee on the Judiciary, United States Senate.
- Mansfield, E. (1986). Patents and innovation: An empirical study. *Management Science* 32(2), 173–181.
- Masters, G. M. (2013). *Renewable and efficient electric power systems*. John Wiley & Sons.
- McFadden, D. (1974). The measurement of urban travel demand. *Journal of Public Economics* 3(4), 303–328.
- Mejer, M. and B. van Pottelsberghe (2012). Economic incongruities in the European patent system. *European Journal of Law and Economics* 34(1), 215–234.
- Merges, R. P. (1999). As many as six impossible patent before breakfast: Property rights for business concepts and patent system reform. *Berkeley Technology Law Journal* 14, 577.
- Moser, P. (2013). Patents and innovation: Evidence from economic history. *Journal of Economic Perspectives* 27(1), 23–44.
- Mullahy, J. (1986). Specification and testing of some modified count data models. *Journal of Econometrics* 33(3), 341–365.
- Nelson, R. R. (1959). The simple economics of basic scientific research. *Journal of Political Economy* 67(3), 297–306.
- Nordhaus, W. (1967). The optimal life of a patent. Discussion Paper 241, Cowles Foundation.
- Nordhaus, W. (2011). Designing a friendly space for technological change to slow global warming. *Energy Economics* 33(4), 665–673.
- Nordhaus, W. D. (1969a). An economic theory of technological change. *The American Economic Review* 59(2), 18–28.
- Nordhaus, W. D. (1969b). *Invention, growth and welfare: A theoretical treatment of technological change*. MIT Press.

- Odam, N. and F. P. de Vries (2020). Innovation modelling and multi-factor learning in wind energy technology. *Energy Economics* 85, 104594.
- OECD (2018). The measurement of scientific, technological and innovation activities – Oslo manual 2018 Guidelines for collecting, reporting and using data on innovation. OECD publications, 4th edition.
- Ospina, R. and S. L. Ferrari (2010). Inflated beta distributions. *Statistical Papers* 51(1), 111.
- Pakes, A. (1985). On patents, R&D, and the stock market rate of return. *Journal of Political Economy* 93(2), 390–409.
- Pakes, A. (1986). Patents as options: Some estimates of the value of holding European patent stocks. *Econometrica* 54(4), 755–784.
- Parisi, M. L., F. Schiantarelli, and A. Sembenelli (2006). Productivity, innovation and R&D: Micro evidence for Italy. *European Economic Review* 50(8), 2037–2061.
- Peterson, E. W. and J. P. J. Hennessey (1978). On the use of power laws for estimates of wind power potential. *Journal of Applied Meteorology and Climatology* 17(3), 390–394.
- Priest, G. L. and B. Klein (1984). The selection of disputes for litigation. *The Journal of Legal Studies* 13(1), 1–55.
- Rouvinen, P. (2002). Characteristics of product and process innovators: Some evidence from the Finnish innovation survey. *Applied Economics Letters* 9(9), 575–580.
- Sakakibara, M. and L. Branstetter (2001). Do stronger patents induce more innovation? Evidence from the 1988 Japanese patent law reforms. *The RAND Journal of Economics* 32(1), 77–100.
- Sampat, B. N. and A. A. Ziedonis (2004). Patent citations and the economic value of patents. In *Handbook of Quantitative Science and Technology Research*, pp. 277–298. Springer.
- Sarja, J. and V. Halonen (2013). Wind turbine selection criteria: A customer perspective. *Journal of Energy and Power Engineering* 7(9), 1795.
- Scherer, F. M. (1982). Inter-industry technology flows and productivity growth. *The Review of Economics and Statistics* 64(4), 627–634.
- Scherer, F. M. (1984). Using linked patent and R&D data to measure interindustry technology flows. In Z. Griliches (Ed.), *R&D, patents and productivity: An international comparison*, pp. 24–38. New York: Harvester Wheatsheaf.
- Schleich, J., R. Walz, and M. Ragwitz (2017). Effects of policies on patenting in wind-power technologies. *Energy Policy* 108, 684–695.

- Schneider, C. (2011). The battle for patent rights in plant biotechnology: Evidence from opposition filings. *The Journal of Technology Transfer* 36(5), 565–579.
- Smithson, M. and J. Verkuilen (2006). A better lemon squeezer? Maximum-likelihood regression with beta-distributed dependent variables. *Psychological Methods* 11(1), 54.
- Spulber, D. F. (2021). *The case for patents*. World Scientific.
- Squicciarini, M., H. Dernis, and C. Criscuolo (2013). Measuring patent quality: Indicators of technological and economic value. Working Paper 2013-3, OECD Science, Technology and Industry.
- Sterlacchini, A. (2016). Patent oppositions and opposition outcomes: Evidence from domestic appliance companies. *European Journal of Law and Economics* 41(1), 183–203.
- Sternitzke, C. (2013). An exploratory analysis of patent fencing in pharmaceuticals: The case of PDE5 inhibitors. *Research Policy* 42(2), 542–551.
- Tandon, P. (1982). Optimal patents with compulsory licensing. *Journal of Political Economy* 90(3), 470–486.
- Tang, T. and D. Popp (2016). The learning process and technological change in wind power: Evidence from China’s CDM wind projects. *Journal of Policy Analysis and Management* 35(1), 195–222.
- Thumm, N. (2004). Strategic patenting in biotechnology. *Technology Analysis & Strategic Management* 16(4), 529–538.
- Train, K. E. (1986). *Qualitative choice analysis: Theory, econometrics, and an application to automobile demand*, Volume 10. MIT press.
- Trajtenberg, M. (1989). The welfare analysis of product innovations, with an application to computed tomography scanners. *Journal of Political Economy* 97(2), 444–479.
- Trajtenberg, M. (1990). A penny for your quotes: Patent citations and the value of innovations. *The RAND Journal of Economics* 21(1), 172–187.
- UNEP (2010). Patents and clean energy: Bridging the gap between evidence and policy. Report, United Nations Environment Programme, joint with the European Patent Office and the International Centre for Trade and Sustainable Development.
- Van der Drift, J. (1988). Statistics of european patents on legal status and granting data. *World Patent Information* 10(4), 243–249.
- Van Pottelsberghe, B. (2011). The quality factor in patent systems. *Industrial and Corporate Change* 20(6), 1755–1793.

- van Zeebroeck, N. and B. van Pottelsberghe (2011). The vulnerability of patent value determinants. *Economics of Innovation and New Technology* 20(3), 283–308.
- Vuong, Q. H. (1989). Likelihood ratio tests for model selection and non-nested hypotheses. *Econometrica* 57(2), 307–333.
- Wright, T. P. (1936). Factors affecting the cost of airplanes. *Journal of the Aeronautical Sciences* 3(4), 122–128.
- Yang, J. (2014). The use and abuse of patents in the smartphone wars: A need for change. *Case Western Reserve Journal of Law, Technology & the Internet* 5, 239–258.
- Zhang, H., Y. Zheng, D. Zhou, and X. Long (2018). Selection of key technology policies for Chinese offshore wind power: A perspective on patent maps. *Marine Policy* 93, 47–53.

* * *

Résumé long

L'innovation est traditionnellement considérée comme le moteur de la croissance économique. En permettant une augmentation de la productivité des facteurs, elle est censée avoir contribué à l'amélioration du niveau de vie depuis des millénaires, et particulièrement depuis la première révolution industrielle. Cependant, le rapport de 1972 sur les limites de la croissance (*Limits to growth*), commandé par le Club de Rome, a ouvert les yeux au monde sur les problèmes environnementaux liés à la poursuite de la croissance économique dans un contexte de ressources limitées. Cinquante ans plus tard, si l'idée de répondre aux défis environnementaux par des modes de vie plus sobres fait son chemin, l'innovation reste un levier important dans l'objectif de maintenir les conditions de vie tout en réduisant la consommation de ressources et les émissions de gaz à effet de serre (GES) associées. L'un des principaux défis est celui de l'orientation des investissements en recherche vers des technologies « propres » ou « vertes », c'est-à-dire respectueuses de l'environnement. D'un point de vue économique, la réalisation de cet objectif nécessite de corriger deux types d'externalités : les externalités technologiques et environnementales. D'une part, le caractère non-rival de la connaissance, ainsi que le coût élevé et l'incertitude associés à sa création, induisent des investissements en recherche inférieurs à ce qui serait socialement souhaitable.¹ D'autre part, les dommages environnementaux causés par les activités polluantes sont peu pris en compte dans les décisions des agents car ils seront supportés par les générations futures.

Paradoxalement, alors qu'elle est considérée comme l'une des solutions au changement climatique, l'innovation en a initialement été un facteur important. En effet, les importantes améliorations du niveau de vie enregistrées depuis la révolution industrielle se sont accompagnées d'une forte augmentation des émissions de gaz à effet de serre. Un exemple notable est celui de l'extraction du charbon, qui a bénéficié d'une invention majeure de la fin du 18^{ème} siècle, à savoir la machine à vapeur. Après avoir permis une baisse du coût du charbon en ouvrant la possibilité d'atteindre des gisements plus profonds, la machine à vapeur

¹D'autres externalités, telles que les externalités informationnelles et d'apprentissage, jouent un rôle important dans les phases aval d'adoption et de diffusion des technologies. Elles ne seront cependant pas étudiées en détail dans ce travail.

a ensuite vu ses usages multipliés, notamment dans le secteur des transports. De nos jours, le charbon est encore assez largement utilisé pour la production d'électricité et est responsable d'une grande partie des émissions de GES dans le secteur de la production électrique au niveau mondial. Les données de la National Oceanic and Atmospheric Administration (NOAA) montrent que la concentration de CO₂ dans l'atmosphère a évolué de 279,6 ppm en l'an 1000 à 288,2 ppm en 1870, puis à 421 ppm en 2022. En conséquence, la température moyenne mondiale a augmenté de près d'un degré Celsius par rapport à l'époque préindustrielle. Depuis sa création en 1988, le Groupe d'experts intergouvernemental sur l'évolution du climat (GIEC) n'a cessé de mettre en garde contre les conséquences alarmantes du changement climatique, qu'elles soient directes (montée du niveau des océans, augmentation de la fréquence des événements extrêmes ou pertes de biodiversité, entre autres) ou indirectes (problèmes de santé par exemple).

Actuellement, le secteur de l'énergie reste un émetteur majeur. Selon les données de l'Agence européenne pour l'environnement (AEE), la production d'énergie était responsable d'environ 25,8% des émissions européennes de GES en 2019. Les principaux objectifs de la politique énergétique européenne sont (i) d'assurer la sécurité énergétique, (ii) de fournir une énergie à prix abordable aux consommateurs finaux, et (iii) de lutter contre le changement climatique.² Les énergies renouvelables semblent répondre simultanément à ces objectifs : les sources d'énergie primaires requises sont (i) fournies par la nature – donc disponibles partout –, (ii) à coût moindre, et (iii) neutres en carbone. En conséquence, l'un des objectifs de l'Union de l'énergie de 2015 est de « promouvoir la recherche dans le domaine des technologies à faible émission de carbone et des technologies énergétiques propres, et de donner la priorité à la recherche et à l'innovation afin de favoriser la transition énergétique et d'améliorer la compétitivité ». La promotion des technologies à faible émission de carbone est par exemple l'un des piliers du Green Deal européen de 2019, dont l'ambition est de réduire les émissions de GES de 55% en 2030 (par rapport au niveau de 1990) et d'atteindre la neutralité carbone en 2050. A cet effet, le Fonds d'innovation créé en 2015 est censé favoriser le développement et la commercialisation de technologies vertes innovantes, notamment les technologies de « production d'énergie renouvelable innovante ». Il est principalement financé par les recettes de la mise aux enchères d'une quantité prédéfinie de quotas du système européen d'échange de quotas d'émission (EU-ETS) (environ 450 millions entre 2020 et 2030 représentant 38 milliards d'euros à 75/tCO₂). Le plus générique programme Horizon Europe (programme de recherche et d'innovation de l'Union Européenne), déployé sur la période 2021-2027, prévoit de consacrer 35% de son budget

²Les autres objectifs incluent l'intégration du marché et l'amélioration dans l'efficacité énergétique.

de 95,5 milliards d'euros à la problématique du changement climatique.³ Ainsi, l'appel à financements « Sustainable, secure and competitive energy supply » (HORIZON-CL5-2021-D3-03), doté de 10 millions d'euros, comprenait 3 défis liés à l'éolien.

Parmi les sources d'énergie renouvelables, le vent est probablement, au même titre que l'eau pour l'hydroélectricité, la plus exploitée. Des voiliers millénaires aux éoliennes actuelles de cent mètres de hauteur en passant par les moulins et les pompes à vent, l'homme a depuis longtemps tiré profit de l'énergie cinétique du vent. La première éolienne, développée par l'inventeur américain Charles F. Brush (1888), était équipée d'une dynamo de 12kW. La dernière turbine Haliade-X de General Electric (GE), qui devrait bientôt être mise en service au sein du parc éolien de Dogger Bank (Royaume-Uni), a une puissance nominale de 14 000 kW. À propos de cette turbine, le site web du parc annonce que « une rotation [...] peut alimenter un foyer britannique pendant deux jours ». Il ne fait nul doute que des efforts de recherche considérables ont été entrepris pour parvenir à un tel résultat. L'Office européen des brevets (OEB) recense 173 121 demandes de brevet déposées dans le monde entre 1890 et 2020 pour l'énergie éolienne (classe Y02E 10/7 de la Classification Coopérative des Brevets). Elles couvrent 102 954 inventions uniques, dont environ 95% ont été découvertes à partir de 1980. D'après la base de données THEWINDPOWER, et en se concentrant sur les avancées technologiques concrètes, les turbines commercialisées avant 1980 avaient une puissance nominale maximale de 600 kW. On peut s'attendre à ce que la tendance à l'augmentation de la puissance nominale des turbines se poursuive car d'ici 2028, selon une étude récente d'IntelStor, le secteur mondial de l'énergie éolienne devrait dépenser 28,2 milliards de dollars en recherche et développement (R&D) privée, qui devraient être complétés par 8,7 milliards de dollars de dépenses publiques.⁴ Selon Wood Mackenzie, les dépenses de R&D des dix principaux fabricants d'éoliennes ont atteint 1,6 milliard d'euros en 2018 et devraient s'élever à 2,3 milliards d'euros d'ici 2023.⁵

L'évolution du nombre d'inventions brevetées dans le monde, mise en évidence par la figure ci-après, suit une trajectoire similaire à celle du développement et de la diffusion des technologies.⁶ L'intérêt marqué pour l'énergie éolienne à partir des années 1970 peut s'expliquer par le soutien public apporté par des pays pionniers tels que le Danemark ou l'Allemagne

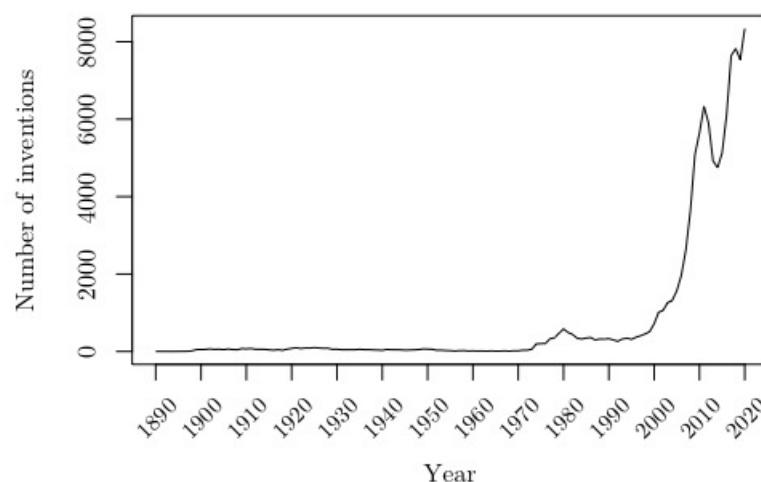
³Le programme Horizon Europe ne doit pas être confondu avec les prix Horizon, qui sont des prix d'innovations distribués par la Commission Européenne. Il visent à la mise en concurrence d'entreprises pour l'atteinte d'un objectif défini à l'avance.

⁴<https://www.windpowerengineering.com/wind-rd-spending-to-top-36-9-billion-by-2028/>, consulté le 12 octobre 2019.

⁵<https://www.woodmac.com/press-releases/top-ten-wind-turbine-oems-to-spend-2.3bn-on-rd-by-2023/>, consulté le 12 octobre 2019.

⁶Le nombre d'inventions correspond au nombre de familles uniques. Une famille de brevets regroupe l'ensemble des brevets couvrant une même invention.

à la technologie éolienne⁷ par le biais d'instruments de soutien par l'offre (*supply-push* ou *technology-push*) et/ou la demande (*demand-pull* ou *market-pull*).⁸ Les instruments de soutien par l'offre visent à encourager les découvertes « radicales » indépendamment des besoins exprimés par les consommateurs. Le crédit d'impôt pour la recherche ou les subventions à la recherche sont des exemples de tels instruments. Ces derniers ont par exemple été mis en œuvre à partir de 1976 au Danemark. L'objectif des instruments de soutien par la demande est de stimuler la demande pour une technologie donnée, ce qui, en augmentant les perspectives de profit, est supposé inciter à l'investissement en R&D. Les systèmes précurseurs des tarifs d'achat garantis font partie de ces instruments et ont par exemple été mis en œuvre depuis 1979 en Allemagne.⁹ La maturité technologique est un facteur important pour faire pencher la balance vers une catégorie spécifique d'instruments : alors que les stratégies d'incitation à l'offre sont pertinentes dans les premières étapes (plus longues et plus incertaines) du processus d'innovation, les instruments d'incitation à la demande exigent la préexistence de connaissances et tendent à favoriser l'innovation incrémentale.



Les chiffres présentés ci-dessus soulèvent deux questions importantes qui seront étudiées en profondeur dans cette thèse. La première concerne les brevets et le progrès technique. Comme nous le détaillerons plus loin, le système des brevets, en récompensant les inventeurs par un droit d'exclure toute tierce personne de l'utilisation de leurs inventions, est supposé

⁷Ces politiques concernaient les énergies renouvelables de manière générale, mais certains facteurs tels que les conditions climatiques ont orienté l'innovation vers la technologie éolienne.

⁸Pour plus d'informations sur ces instruments et leur évolution, se référer par exemple à [Godin and Lane \(2013\)](#).

⁹Il est intéressant de noter que les fabricants d'éoliennes de ces pays (par exemple, la société danoise Vestas et les sociétés allemandes Enercon et Nordex) sont toujours des entreprises leaders sur le marché.

inciter les agents économiques à s'impliquer dans des activités de recherche. Le fait qu'entre 1890 et 1980, 5% des inventions brevetées ont contribué à multiplier par 50 la puissance nominale des turbines (de 12kW à 600kW) alors que les 95% restants, brevetés entre 1980 et 2020, ont conduit à une augmentation d'un facteur d'environ 23 (de 600kW à 14 000kW) peut amener à s'interroger sur la pertinence d'un tel système. Si ce phénomène particulier peut s'expliquer par des rendements marginaux décroissants ou des changements dans le contexte économique, la littérature économique a depuis longtemps émis des doutes sur la capacité du système des brevets à remplir sa fonction originelle de catalyseur de l'innovation et du progrès technique. La seconde question concerne le nombre de brevets en tant que résultat des politiques d'innovation, et en particulier d'innovation verte. Une augmentation dans le nombre de brevets en réponse à la mise en œuvre d'une politique reflète-t-elle l'efficacité de cette politique ? Une fois encore, les résultats des contributions précédentes sont ambigus. En particulier, il a été souligné que (i) toutes les inventions ne font pas l'objet d'une protection par brevet, et (ii) il existe une hétérogénéité dans la valeur sociale générée par les inventions brevetées. L'exercice auquel nous nous sommes livrés en commentant la figure ci-dessus à la lumière de la politique environnementale est donc un exercice délicat. Les sections suivantes approfondissent ces questions et présentent l'état de l'art académique en la matière.

Le brevet comme réponse aux externalités de connaissance

On considère généralement que la promulgation en 1474 de la *Parte Veneziana* a ouvert la voie aux systèmes de brevets actuels. Bien que la pratique ait anticipé la formulation économique des questions d'innovation, un système de brevets se justifie aisément du point de vue économique. La théorie économique a montré - sur la base de [Nelson \(1959\)](#) et [Arrow \(1962\)](#) - qu'une situation de laissez-faire induit un sous-investissement dans les activités de R&D et a souligné la nécessité d'encourager les entreprises à s'engager dans la création de connaissance. Ce phénomène résulte du problème dit d'appropriabilité dont la source est double. D'une part, le processus d'innovation est incertain en plus d'être coûteux.¹⁰ Un agent rationnel ne mobilisera les ressources nécessaires que si la valeur attendue de l'innovation¹¹ qui en résulte dépasse le coût de ces ressources. D'autre part, la connaissance a les caractéristiques d'un bien public. En effet, elle est intrinsèquement non-rivale (c'est-à-dire que l'utilisation de la connaissance par un agent n'empêche pas son utilisation

¹⁰De plus, les coûts de recherche peuvent être considérés comme des coûts irrécupérables. Ainsi, l'investissement nécessaire à la création de la connaissance ne peut être recouvert que par la monétisation de la connaissance (commercialisation de l'innovation qui en découle ou cession/concession des droits de propriété intellectuelle associés).

¹¹Dans une perspective schumpétérienne, on considère qu'une innovation est la réalisation commerciale d'une invention.

par un autre) ainsi que non-excluable (c'est-à-dire qu'il est impossible – ou du moins très coûteux – de restreindre l'accès à la connaissance). La première propriété implique que la connaissance peut être reproduite sans coût (ou seulement celui de la compréhension). La seconde propriété rend possible sa mise en œuvre par des concurrents potentiels qui, contrairement à l'inventeur original, n'ont pas supporté les coûts inhérents à sa création. Cela peut conduire à une situation dans laquelle le prix de l'innovation est tel que l'inventeur n'est pas en mesure de couvrir son investissement alors que les imitateurs réalisent des profits positifs. Dans un tel contexte, l'intérêt de chacun est d'attendre que l'invention soit découverte par quelqu'un d'autre et personne n'est prêt à s'impliquer dans le processus de recherche. Le régulateur est donc confronté à un problème typique de passager clandestin.

Cependant, la capacité d'exclure les tiers de l'utilisation d'une idée nouvelle dépend de la possibilité de *rétro-ingénierie* (*reverse engineering*). Dans un contexte de veille technologique, elle consiste à démonter la version finale d'une innovation pour en extraire le principe novateur. Plus l'effort nécessaire pour (re)découvrir le contenu de l'invention est important, plus l'exclusion est facile. Dans les cas où la *rétro-ingénierie* est complexe, le secret commercial peut suffire à l'inventeur pour empêcher l'imitation de l'idée sous-jacente. Sinon, un système de brevets fait sens dans la mesure où il permet de rendre la connaissance excluable. Un brevet peut être défini comme un droit d'exclure tout tiers de toute utilisation de l'invention brevetée. Tant que le brevet est actif, son titulaire a la possibilité de restreindre l'accès à l'invention – jouissant ainsi d'un pouvoir de marché dû à une position de monopole ou à une stratégie de différenciation –, ou de demander des redevances pour cet accès. Il est intéressant de noter qu'il a également la possibilité de fournir un accès libre à l'invention, ce qui rend les brevets complémentaires des systèmes d'innovation ouverts. Avec un tel système, l'incitation à innover s'accompagne d'une perte sèche socialement nuisible. Dans la suite de ce document, cette perte sera appelée le *coût social* du système de brevets. Le brevet est donc un instrument de second rang et la question du design optimal (compromis entre *inefficacité statique* et *efficacité dynamique*) a été soulevée de longue date par les travaux fondateurs de Nordhaus (1967, 1969b), qui ont donné naissance à une abondante littérature. La recherche des niveaux optimaux de *longueur* (c'est-à-dire de durée de vie), de *largeur* (c'est-à-dire la portée technologique du brevet) et de *hauteur* (c'est-à-dire le degré de nouveauté dans les cas d'innovations progressives) des brevets a contribué à façonner nos systèmes actuels : une durée de vie limitée (jusqu'à 20 ans dans la plupart des pays), des revendications définissant l'étendue de la protection et des critères de brevetabilité (nouveauté, inventivité et utilité/application industrielle).

Une autre préoccupation à laquelle le système des brevets est supposé répondre est celle de la diffusion de l'innovation. En effet, la protection par brevet est conditionnée à la

divulgaration des caractéristiques de l'invention de telle sorte qu'elle puisse être reproduite par une « personne du métier ». En ce sens, le système est censé éviter le gaspillage de ressources en « réinventant la roue » et inciter les concurrents à « contourner » les brevets existants (c'est-à-dire à trouver d'autres moyens de résoudre le même problème). En outre, il permet une diffusion plus rapide de l'innovation une fois que l'invention brevetée est tombée dans le domaine public¹² et favorise *l'innovation incrémentale*.¹³ La question de la diffusion des technologies est étroitement liée à celle des *spillovers* de connaissance. Cette dernière traduit l'idée selon laquelle les efforts de recherche engagés par d'autres entreprises peuvent permettre à une entreprise donnée d'obtenir des résultats à moindre effort (Jaffe, 1986). Ce phénomène est inhérent à la nature de bien public de la connaissance et constituait la justification de base du recours aux systèmes de brevets. Cependant, le célèbre article de Cohen and Levinthal (1989) a contribué à nuancer « l'effet d'incitation négative » (*negative incentive effect*) des *spillovers* et à remettre en question le système des brevets dans un tel contexte. Les auteurs soulignent le fait que la R&D, en plus de contribuer à la création de connaissances, peut être mobilisée pour augmenter la *capacité d'absorption* des entreprises, c'est-à-dire leur capacité à comprendre et à mettre en œuvre les idées des autres. Ainsi, l'effet d'incitation négatif serait surestimé car l'existence de *spillovers* catalyserait, dans une certaine mesure, les investissements de R&D. Néanmoins, Jaffe et al. (2000) soulignent que si l'existence de *spillovers* était acceptée depuis longtemps, peu de recherches ont été menées pour comprendre les canaux par lesquels les connaissances circulent. En se basant sur des données d'enquête, ils montrent que les données sur les citations de brevets sont un indicateur acceptable de la communication entre inventeurs et des *spillovers* de connaissances qui en découlent. Dans ce contexte, un système de brevets et la publication obligatoire des caractéristiques des inventions qui y est associée pourraient exacerber l'externalité (positive) des *spillovers*. Une diffusion accrue des technologies peut être obtenue par le biais de l'octroi de licences obligatoires pour les technologies, qui a des fondements théoriques (voir par exemple Tandon, 1982) et des applications pratiques : l'octroi de licences obligatoires pour les produits pharmaceutiques est prévu dans l'accord de 1995 sur les aspects des droits de propriété intellectuelle qui touchent au commerce. Bien qu'importants et intéressants, ces volets de la littérature dépassent le cadre de cette thèse.¹⁴ Enfin, le fait que le contenu des brevets soit public par définition fait des brevets

¹²À cet égard, d'un point de vue social, les brevets présentent un avantage par rapport au temps d'avance et au secret.

¹³Certaines études (e.g. Bessen and Maskin, 2009) montrent que dans un tel cadre séquentiel, le système des brevets peut ne pas fournir les bonnes incitations.

¹⁴La question des transferts de technologie sera toutefois abordée dans la prochaine sous-section comme un défi important en matière de justice climatique.

une source abondante de données largement utilisée pour refléter l'activité inventive des entreprises ou des pays (Griliches, 1990).

Compte tenu du coût social du système des brevets, de nombreuses contributions se sont attachées à examiner empiriquement s'il était un instrument efficace pour stimuler l'innovation. Machlup (1958) a écrit ce qui pourrait être traduit par :

Si nous n'avions pas de système de brevets, il serait irresponsable, sur la base de notre connaissance actuelle de ses conséquences économiques, de recommander d'en instituer un. Mais puisque nous avons un système de brevets depuis longtemps, il serait irresponsable, sur la base de nos connaissances actuelles, de recommander de l'abolir.

Cette citation bien connue reflète parfaitement la complexité de la question. Plus récemment, des contributions remarquées de Boldrin and Levine (2008, 2013) ont souligné les faiblesses d'un tel système au point d'en recommander l'abolition.¹⁵ Ils soutiennent que les brevets freinent l'innovation au lieu de la promouvoir. Tout d'abord, ils soulignent qu'à long terme, l'accumulation de brevets décourage indubitablement les inventeurs actuels et futurs d'entrer sur les marchés concernés en raison des menaces constantes de litiges et de la nécessité de négocier des licences. En outre, les comportements de recherche de rente des entreprises peuvent exacerber ce phénomène. L'idée est que les entreprises peuvent utiliser les brevets comme un moyen de conforter leur position sur le marché ou de s'accaparer des rentes (indues ?) de monopole.¹⁶ Ces comportements peuvent prendre diverses formes. Par exemple, les brevets défensifs sont des brevets déposés ou acquis par une entreprise pour se parer contre d'éventuels litiges en s'assurant de pouvoir soit (i) proposer une option gagnant-gagnant de licence croisée, soit (ii) menacer les plaignants potentiels de litige concernant un autre brevet. En alimentant le « maquis de brevets » (*patent thicket*),¹⁷ de tels usages « abusifs » des brevets peuvent finalement entraver l'innovation.¹⁸ Plus généralement, ce phénomène est mieux connu sous le nom de *tragédie des anticommons* (Heller and Eisenberg, 1998) : de nouvelles technologies (potentiellement à forte valeur sociale) peuvent ne pas émerger en raison de la répartition disparate des brevets nécessaires.¹⁹ Une

¹⁵La publication plus récemment encore de *The Case for Patents* par Spulber (2021) traduit un regain d'intérêt pour cette question, avec un point de vue opposé.

¹⁶La notion de *preemptive patenting*, au sens de Gilbert and Newbery (1982), en est un bon exemple.

¹⁷On dit qu'une personne est confrontée à un *maquis de brevets* lorsque la production d'un bien nécessite des accords de licence avec de nombreux titulaires de brevets sur de nombreuses inventions. Par exemple, un smartphone est susceptible de contenir environ 250 000 brevets selon certaines estimations (Yang, 2014).

¹⁸C'est particulièrement le cas lorsque les frontières de la protection sont mal définies. Ceci est au cœur du concept de *brevet probabiliste* développé par Lemley and Shapiro (2005).

¹⁹L'absence de coopération entre les détenteurs de brevets implique une *double marge* qui entraîne une augmentation du coût de mise en œuvre de la technologie sous-jacente.

solution possible à ce problème est la formation d'un *pool* de brevets dans lequel les brevets liés à une technologie spécifique font l'objet de licences croisées par leurs propriétaires afin d'en faciliter l'accès et, en fin de compte, de favoriser le développement technologique. Au début du 20^{ème} siècle, on considère que la guerre des brevets qui a opposé les frères Wright à d'autres pionniers de l'aviation (dont Glen Curtiss) a entravé le développement de l'industrie aéronautique américaine. En 1917, le gouvernement américain les a incités à former un *pool* de brevets, la Manufacturer's Aircraft Association, débloquent ainsi le secteur et permettant la fabrication d'avions pour participer à l'effort de guerre (Freiwald, 2013).

Un autre argument des détracteurs des brevets est qu'il y a peu de preuves qu'un renforcement de la protection par le brevet ait permis de stimuler l'innovation. Si des anecdotes comme celle de l'industrie aéronautique sont utiles pour mettre en évidence les problèmes soulevés par le système des brevets, tirer des conclusions générales est plus complexe à plusieurs égards. Premièrement, l'efficacité du système des brevets en tant que catalyseur de l'innovation dépend fortement du domaine concerné. Par exemple, il est bien établi que la protection par brevet est plus importante dans le secteur pharmaceutique que dans d'autres secteurs (voir, par exemple, l'étude classique de Mansfield, 1986).²⁰ Au sein même d'un secteur donné, l'importance des brevets en tant qu'instrument d'appropriation dépend de la nature des inventions. Cohen et al. (2000) montrent par exemple que les brevets sont mieux adaptés pour protéger des innovations de produit que des innovations de procédé²¹ (par ailleurs, le temps d'avance et le secret apparaissent comme des mécanismes privilégiés dans les deux cas). Enfin, les entreprises peuvent avoir des stratégies de brevetage différentes. L'étude de Arundel (2001) souligne le fait que les grandes entreprises sont plus susceptibles de valoriser la protection par brevet par rapport au secret. Deuxièmement, la mesure du progrès technique présente des enjeux importants. Quels sont les attendus d'un système de brevets ? En premier lieu, il doit fournir des incitations à investir dans les activités de R&D. Les dépenses de R&D semblent être la mesure la plus appropriée pour évaluer un système de brevets. Mais, pour aller plus loin, il est également souhaitable d'apprécier si le système permet des avancées techniques concrètes. En effet, les dépenses

²⁰Dans plusieurs pays, l'industrie pharmaceutique est soumise à un régime spécial en vertu duquel les inventions peuvent faire l'objet d'une demande de certificat complémentaire de protection qui prolonge la durée de vie des brevets associés. Ceci se justifie par le fait que l'obtention d'une autorisation de mise sur le marché est un processus long qui retarde la commercialisation des inventions.

²¹L'innovation de produit est censée soit (i) ouvrir de nouveaux marchés, soit (ii) améliorer les caractéristiques des biens existants. L'innovation de procédé est censée réduire le coût des technologies. Par exemple, Cohen and Klepper (1996b) considère que la R&D conduit à une augmentation de la marge sur coût des prix : l'innovation de produit permet une plus grande qualité qui justifie de facturer un prix plus élevé pour le produit sous-jacent, tandis que l'innovation de procédé contribue à diminuer la marge sur coût de production de ce même bien.

de R&D sont l'intrant du processus d'innovation et englobent l'incertitude inhérente au processus de recherche. Pour pallier à cela, les chercheurs ont étudié l'impact du nombre de brevets ou du renforcement des droits de propriété intellectuelle sur le nombre d'inventions, la productivité totale des facteurs ou le nombre de brevets eux-mêmes. Cette littérature fournit des résultats ambigus. Moser (2013) constate que les pays ne disposant pas d'un système de brevets ne se sont pas révélés moins innovants au regard du nombre d'innovations introduites aux expositions universelles au 19^{ème} siècle, mais montre des différences dans la direction de l'innovation. Kanwar and Evenson (2003) mettent en évidence, au niveau des pays, une relation positive et non ambiguë entre les dépenses de R&D et un indice de « rigueur » de la propriété intellectuelle (PI). Toujours en ce qui concerne les dépenses de R&D, Sakakibara and Branstetter (2001) montrent que les entreprises japonaises n'ont pas été sensibles au renforcement des droits de PI en 1988. Baudry and Dumont (2017) illustrent une corrélation positive entre le nombre de brevets et la productivité du travail au niveau du pays, mais cette relation ne tient pas lorsque l'on considère la productivité totale des facteurs.

Une question connexe concernant le système des brevets réside dans l'hétérogénéité dans la valeur ou la qualité des inventions brevetées. Sur la base de cette observation, les chercheurs se sont fortement appuyés sur ce qu'on appelle les *métriques* de brevets pour rendre compte de cette hétérogénéité (voir Squicciarini et al., 2013, pour un aperçu des métriques les plus courantes). La « qualité » des brevets est un concept multidimensionnel qui ne fait toujours pas l'objet d'une définition consensuelle. La valeur d'un brevet peut être décomposée en sa valeur sociale et sa valeur privée. La valeur sociale d'une innovation peut être définie à la manière de Trajtenberg (1990) : les avantages sociaux générés par l'innovation, sous la forme de surplus additionnel du consommateur et des profits découlant de l'innovation. En se concentrant sur les scanners de tomographie, il mesure le bien-être généré par l'ensemble des produits disponibles à une année donnée, relativement à l'année précédente. Il observe que, bien qu'elle ne soit pas corrélée à un comptage simple des brevets, la valeur du bien-être est corrélée au nombre de brevets pondéré par les citations *forward*. L'appréciation du fait qu'un brevet remplit ou non les critères de brevetabilité est basée sur l'état de l'art. Si une invention repose sur des connaissances antérieures, l'identification et la citation des brevets associés sont utiles pour évaluer la nouveauté et l'activité inventive d'une invention. Un brevet fortement cité est donc susceptible d'avoir eu un impact important dans son domaine. Le nombre de citations reçues, s'il est corrigé des *autocitations*, est qui plus est indépendant du titulaire du brevet et présente donc l'avantage d'être à l'abri d'éventuelles manipulations. À l'inverse, la valeur privée est généralement abordée par des mesures sur lesquelles le demandeur a la main. Par exemple, Pakes (1986) s'appuie sur les données de

renouvellement pour évaluer la valeur privée des brevets. Comme le maintien d'un brevet nécessite l'acquittement de frais réguliers, les décisions de renouvellement apportent une information sur les attentes du titulaire concernant les retombées de l'invention, car elles reflètent le consentement à payer de l'entreprise pour la protection. Il est intéressant de noter que la valeur sociale et la valeur privée peuvent être déconnectées : par exemple, un brevet protégeant une invention marginale (c'est-à-dire ayant une faible valeur sociale) peut présenter l'avantage de bloquer le développement économique de concurrents (et donc avoir une valeur privée élevée). Cependant, distinguer la valeur sociale de la valeur privée sur la base de la métrique des brevets peut s'avérer difficile. Par exemple, [Harhoff et al. \(2003\)](#) trouvent que les citations *forward* sont positivement associées à la valeur des brevets telle que déclarée par les entreprises elles-mêmes. Dans la même veine, [Hall et al. \(2005\)](#) ont montré en utilisant la méthode du q de Tobin que le nombre de citations reçues par brevet est positivement lié à la valeur boursière des entreprises. [Sampat and Ziedonis \(2004\)](#) évaluent la valeur « économique » des brevets par (i) le fait pour un brevet d'être licencié et, si tel est le cas, (ii) le revenu issu de la licence. Leurs résultats montrent que les citations de brevets sont un bon indicateur du fait qu'un brevet soit licencié ou non, mais pas du revenu subséquent. [Abrams et al. \(2013\)](#), en utilisant des données sur les revenus de licences de brevets, mettent en évidence une relation en U inversé entre les citations reçues et valeur des brevets. Ils affirment que ce résultat est lié au fait que les brevets de grande valeur font l'objet d'un brevetage stratégique par les titulaires pour décourager l'entrée sur le marché, ce qui se traduit par un nombre moindre de citations.

Bien que certains d'entre eux soient en dehors du cadre de cette thèse, toutes les questions génériques liées aux brevets mentionnées dans cette section sont cruciales pour permettre l'émergence, l'amélioration et la diffusion des technologies, et notamment celles à faible émission de carbone. La section suivante traite de la place des brevets dans les défis environnementaux actuels, en particulier ceux liés à l'énergie.

Le rôle des brevets dans la transition énergétique

Il a été mentionné plus haut que l'innovation environnementale est confrontée au problème de la *double externalité*, selon lequel promouvoir l'innovation verte implique de s'attaquer à deux types d'externalités (technologiques et environnementales). Des recherches associées se sont demandées si les technologies vertes nécessitaient des instruments de soutien spécifiques. [Jaffe et al. \(2005\)](#) se concentrent sur le lien entre les politiques environnementales et d'innovation et concluent que la politique environnementale seule, bien qu'ayant pour effet secondaire de fournir des avantages technologiques aux technologies propres, pourrait ne pas être suffisante pour orienter les investissements de recherche. Les arguments des auteurs

en ce sens concernant la nature de bien public de l'environnement (qui justifierait un soutien public spécifique et plus important), l'absence d'action réelle en matière de politique climatique, l'acceptation politique plus grande de la politique d'innovation par rapport à la politique environnementale, le caractère dynamique de cette dernière (que les politiques actuelles ne parviendraient pas à prendre en compte) et la nature globale du changement climatique. En revanche, Nordhaus (2011) défend ce qu'il qualifie de *price fundamentalism*, à savoir l'idée qu'une fois l'externalité environnementale parfaitement corrigée (par une tarification du carbone), les technologies à faible émission de carbone ne nécessitent pas de soutien extraordinaire par rapport aux technologies « traditionnelles » pour émerger. Cependant, l'auteur lui-même admet que le *price fundamentalism* ne tient que sous une série d'hypothèses assez fortes. Notamment, il dépend fortement de la capacité de la politique environnementale à fixer le « bon » prix du carbone, c'est-à-dire celui qui internaliserait totalement les dommages environnementaux associés, ce qui s'est avéré être difficile en pratiques.²² Les travaux de Acemoglu et al. (2012) soulignent également la nécessité d'une politique d'innovation qui favoriserait les technologies vertes par rapport aux technologies conventionnelles, notamment en raison d'une *state dependence* qui implique une rentabilité et une productivité accrues pour les technologies pour lesquelles le stock de connaissances est plus conséquent. Fischer and Newell (2008) soulignent également le fait que, si la tarification des émissions est la politique la plus efficace pour réduire les émissions, le portefeuille optimal de politiques comprend à la fois des instruments de tarification des émissions et des subventions à la R&D verte. Bien que la plupart de ces études se concentrent sur des instruments autres que le brevet pour encourager la R&D privée,²³ le système des brevets est en arrière plan de toute politique d'innovation. Par exemple, l'Agence internationale pour les énergies renouvelables (IRENA, 2013) a souligné le rôle essentiel des droits de propriété intellectuelle dans la transition énergétique, et en particulier pour stimuler l'innovation dans les technologies des énergies renouvelables.

Par ailleurs, certains auteurs ont envisagé de remodeler le système des brevets afin de s'attaquer au problème du changement climatique. Gerlagh et al. (2014) prolongent les travaux de Acemoglu et al. (2012) et considèrent que la durée des brevets peut être adaptée pour favoriser le développement de technologies propres.²⁴ En ce sens, les décideurs

²²Dans ce cas, il est nécessaire que les technologies vertes soient particulièrement encouragées. L'auteur affirme qu'une solution possible à cet effet serait de prolonger la durée de vie des brevets verts.

²³Un système de brevets peut être considéré comme moins flexible que, par exemple, les subventions à la recherche. Dans la pratique, la plupart des politiques liées aux brevets concernent la « boîte à brevets » (*patent box*), qui consiste à appliquer aux revenus provenant de la concession de licences ou du transfert de brevets un taux d'imposition préférentiel.

²⁴Dans leur article, Acemoglu et al. (2012) considèrent que les inventeurs qui réussissent sont récompensés par un brevet d'un an et que les subventions à la R&D sont le seul moteur de la politique d'innovation.

politiques peuvent s'appuyer sur un portefeuille de politiques plus large : si le montant des subventions à la recherche est fixe, la durée de vie des brevets devrait être adaptée de manière dynamique en fonction du stade de développement de la technologie. En particulier, la durée de vie des brevets devrait être plus élevée aux premiers stades du développement technologique, puis diminuer. Inversement, une durée constante et limitée des brevets devrait être associée à des subventions à la recherche dont le montant diminue avec le développement technologique.²⁵ [Langinier and Ray Chaudhuri \(2019\)](#) examinent, en présence d'une politique de taxation des émissions, les conditions sous lesquelles la réduction des coûts des brevets et le renforcement des critères de brevetabilité conduisent à une réduction du niveau des émissions. L'un de leurs résultats est que, pour un taux de taxe sur les émissions supérieur à un certain seuil, l'introduction d'un système de brevets peut conduire à une augmentation du niveau d'émission. Cet effet peut être atténué en réduisant le coût des brevets pour les technologies vertes, par exemple en accélérant le traitement des demandes de brevets verts.²⁶ Les travaux de [Bonnet \(2016\)](#) reposent sur l'idée qu'une taxe carbone pigouvienne n'est efficace que dans les cas où le marché des biens polluants est concurrentiel. L'auteur affirme en outre qu'un système de brevets crée des distorsions, ce qui implique un cadre de concurrence imparfaite. Dans ce contexte, le régulateur devrait concevoir conjointement des politiques environnementales et d'innovation (respectivement le niveau de taxation et la durée et l'étendue des brevets) afin de soutenir efficacement l'innovation à faible intensité de carbone. La mise en pratique de cette approche pourrait toutefois être entravée par le fait que différentes institutions sont responsables des politiques environnementales et d'innovation. À cet égard, [Choi et al. \(2022\)](#) considèrent une industrie polluante dans laquelle un office des brevets gère la politique des brevets (c'est-à-dire fixe la longueur des brevets) et qu'une agence environnementale est chargée de corriger les externalités environnementales en taxant les émissions. Ils montrent que, dans les industries polluantes non sujettes à politique environnementale, augmenter la durée de vie des brevets peut conduire à réduire la pollution. Ceci est dû au fait que le niveau de production, et les émissions associées, sont plus faibles en situation de monopole conférée par le brevet que lorsque l'invention peut être répliquée par les concurrents. En revanche, lorsqu'une

²⁵D'une certaine manière, cette idée d'augmenter la durée des brevets a déjà été mise en œuvre dans l'industrie pharmaceutique. En effet, les brevets de médicaments peuvent faire l'objet d'un certificat complémentaire de protection qui prolonge la protection maximale du brevet de 20 à 25 ans en Europe. Cette mesure est destinée à compenser le temps nécessaire à l'obtention de l'autorisation de mise sur le marché des médicaments.

²⁶Certains offices de brevets offrent la possibilité aux inventeurs de technologies propres d'accélérer le traitement de leurs demandes de brevets, c'est-à-dire de demander un examen plus rapide. Outre la réduction des asymétries informationnelles, cela permet de diminuer le coût d'opportunité imputable à la procédure d'examen (perte de profit pendant que l'examen est en cours). [Dechezleprêtre \(2013\)](#) fournit des informations sur ces politiques et analyse les impacts de leur mise en œuvre en matière de diffusion des technologies.

politique environnementale s'applique, la longueur optimale des brevets dépend du poids accordé aux dommages environnementaux par chacune des agences. Enfin, bien que cela n'entre pas dans le cadre de cette thèse, il est utile de noter que les brevets sont appelés à jouer un rôle majeur dans le transfert des technologies et sont, par conséquent, importants pour les questions de justice climatique.

Au-delà des usages des brevets à des fins de politique publique, leur utilisation pour évaluer les résultats des politiques d'innovation ou environnementales est courante. Par exemple, les études sur l'innovation dans le seul secteur de l'énergie éolienne s'appuient largement sur les données relatives aux brevets pour évaluer différents aspects du processus d'innovation : les *spillovers* de connaissances (Braun et al., 2010; Grafström, 2018), l'apprentissage par la recherche (Tang and Popp, 2016; Grafström and Lindman, 2017; Odam and de Vries, 2020), les transferts de technologie (Haščič and Johnstone, 2011), les évaluations de politiques environnementales (Johnstone et al., 2010; Lindman and Söderholm, 2016; Schleich et al., 2017; Zhang et al., 2018; Lin and Chen, 2019), les trajectoires technologiques (Huenteler et al., 2016), le développement technologique et maturité des marchés (Dubarić et al., 2011; Baudry and Dumont, 2016), ou encore l'efficacité de la R&D (Kapoor et al., 2012). L'utilisation du nombre de brevets comme indicateur de l'innovation « verte » a été favorisée par la mise en œuvre en 2013 de la classification coopérative des brevets (CPC) par l'Office européen des brevets (OEB) et l'Office des brevets et des marques des États-Unis (USPTO). Contrairement à la classification internationale des brevets (CIB) largement utilisée, la CPC permet, comme cela avait déjà été recommandé par le Programme des Nations unies pour l'environnement (UNEP, 2010), d'identifier directement les brevets liés aux technologies à faible émission de carbone par le biais de la classe Y02, à savoir « Technologies ou applications pour l'atténuation ou l'adaptation au changement climatique ». Une telle distinction permet par exemple d'analyser l'orientation de la recherche vers des technologies respectueuses de l'environnement. La récente publication de l'Agence internationale de l'énergie (IEA, 2021), conjointement avec l'OEB, est un bon exemple de ce phénomène. Mais ces usages des brevets se heurtent aux problèmes mentionnés plus haut. Rappelons qu'il existe deux bonnes raisons pour lesquelles les brevets ne parviendraient pas à refléter réellement le progrès technique. Premièrement, toutes les inventions ne sont pas brevetées car, dans certains cas, le secret ou le temps d'avance peuvent être privilégiés afin d'assurer l'appropriation des bénéfices de la R&D. Deuxièmement, toutes les inventions brevetées n'ont pas la même valeur pour la société et, même si le nombre de brevets est aujourd'hui généralement corrigé par certaines métriques, il existe peu de preuves que ces chiffres corrigés sont corrélés avec le progrès technique. Cela vient du fait que le progrès technique est un concept multidimensionnel et que certaines de ses dimensions peuvent ne pas être

directement mesurées par des paramètres quantifiables. Du moins, les informations requises à cette fin seraient très coûteuses à collecter. À l'inverse, les données sur les brevets sont disponibles en abondance. En effet, outre le fait que les brevets doivent être divulgués publiquement, les offices de brevets ont pour objectif de fournir le plus large accès possible à leur contenu.

Il est donc d'une grande importance d'évaluer si les brevets reflètent correctement le progrès technique, en particulier dans les technologies vertes, qui devraient émerger et se développer pour limiter le climat et ses conséquences, et qui font l'objet d'un soutien public massif à cette fin.

Structure de la thèse et résumé des chapitres

Dans cette thèse, nous nous interrogeons sur la pertinence du recours au brevet, à la fois pour stimuler et pour mesurer l'ampleur et l'orientation du progrès technique. La confrontation des données de brevets avec des mesures objectives du progrès technique effectif est un exercice utile à cet effet. Nous nous concentrons sur l'usage des brevets par les entreprises de l'industrie éolienne européenne afin d'évaluer (i) s'il est utile de renforcer les droits de propriété intellectuelle pour les technologies vertes, et (ii) si les données de brevets peuvent être utilisées de manière sûre pour refléter le progrès technique dans le domaine. Ce travail s'appuie sur les brevets déposés auprès de l'OEB, qui offre aux inventeurs la possibilité de protéger leurs inventions dans plusieurs pays par le biais d'une procédure centralisée.²⁷ Le fait de se concentrer sur les brevets de l'OEB présente plusieurs avantages. Premièrement, toutes les informations concernant ces brevets sont fournies de manière exhaustive par l'OEB *via* la base de données PATSTAT. Deuxièmement, il est considéré que le marché géographique pertinent pour les fabricants d'éoliennes situés dans les pays européens est l'Espace économique européen (EEE).²⁸ Dans ce contexte, on peut s'attendre à ce que les innovations importantes soient protégées au niveau européen. Troisièmement, les brevets supranationaux sont généralement considérés comme des brevets particulièrement précieux. Comme le coût de la protection augmente avec le nombre de juridictions visées, le fait de demander une protection dans plusieurs pays reflète le consentement à payer de l'inventeur pour la protection et donc les retombées économiques espérées de l'invention. De plus, l'OEB est souvent considéré comme un « *gold standard* » concernant la qualité de

²⁷Pour l'instant, l'OEB est chargé d'examiner les demandes de brevet et, le cas échéant, d'accorder la protection par brevet. Dans ce cas, les brevets obéissent à la législation respective des pays visés. Le futur *brevet unitaire* européen, qui devrait entrer en vigueur au printemps 2023 dans les pays participants, aura en revanche un effet unitaire dans l'ensemble de la zone.

²⁸Voir par exemple le cas M.8134 de la Commission européenne concernant la fusion entre Siemens et Gamesa en 2016.

sa procédure d'examen, qui mobilise trois examinateurs.²⁹

Le chapitre 1 se concentre sur le « côté obscur » du système des brevets et aborde la question de ses usages dits stratégiques. [Lanjouw and Schankerman \(2001\)](#) ont montré que les litiges relatifs aux brevets apportent des indications utiles dans cet objectif puisqu'ils reflètent les stratégies des entreprises pour capturer la *rente d'innovation*. Dans cette étude, nous tirons profit des données sur les oppositions de brevets fournies par la base de données PATSTAT de l'OEB. La procédure d'opposition à l'OEB permet à toute tierce partie de réclamer l'invalidité d'un brevet dans les 9 mois suivant la délivrance de ce dernier. L'OEB réexamine alors le contenu du brevet sous-jacent et doit décider de le maintenir, de l'amender ou de le révoquer. Dans la même veine que le litige, l'opposition est fondée sur un désaccord concernant un brevet particulier entre son titulaire et un tiers. Toutefois, la décision concernant l'opposition s'applique simultanément dans tous les pays, tandis que le litige nécessite un règlement spécifique à chaque pays. Elle a l'avantage de faciliter la collecte des données et de permettre une analyse supranationale. Toutefois, les montants en jeu sont généralement moins élevés dans une procédure d'opposition que dans les cas de litige ([Mejer and van Pottelsberghe, 2012](#)). Sur la base d'un échantillon de brevets liés à l'énergie éolienne déposés auprès de l'OEB, nous analysons d'abord l'impact des caractéristiques du brevet et du demandeur sur la probabilité et l'étendue de l'opposition (l'étendue de l'opposition étant le nombre d'opposants uniques à un même brevet). Un résultat important est que les brevets ayant une valeur privée élevée, telle qu'approchée par leur portée géographique, sont plus susceptibles de faire l'objet d'oppositions. Dans la deuxième partie, l'analyse des déterminants des résultats des oppositions renseigne sur le caractère stratégique des oppositions. En effet, des oppositions « fictives » peuvent être dirigées vers des brevets de valeur afin de retarder la commercialisation des produits associés ou de créer de l'incertitude parmi les concurrents. Sur la base de régressions beta, dans lesquelles la variable dépendante est la part des revendications maintenues à la suite de l'opposition, nous observons que les brevets ayant une valeur privée élevée sont également moins susceptibles de résister aux oppositions. Ceci suggère que les oppositions dans l'industrie de l'énergie éolienne sont légitimes plutôt que stratégiques et que la procédure d'opposition est principalement utilisée pour éliminer les brevets indus. En outre, nous proposons une mesure du caractère défensif des brevets basée sur la distance technologique entre un brevet particulier et le portefeuille de son titulaire. En effet, les stratégies défensives de blocage pourraient consister à construire un mur de brevets autour d'une invention importante afin de sécuriser une position technologique, ce qui pourrait finalement entraver le développement de la technologie d'une manière plus prononcée encore (que celle de la protection d'une seule invention). Nous soutenons qu'en

²⁹Voir [Van Pottelsberghe \(2011\)](#) pour plus d'informations.

présence de telles stratégies, les brevets qui sont proches du cœur technologique de leur propriétaire devraient être plus susceptibles de faire l'objet d'une opposition. Cependant, nos résultats ne prouvent pas l'existence de telles stratégies.

Si les usages stratégiques des brevets ne semblent pas être monnaie courante dans l'industrie de l'énergie éolienne, on peut néanmoins se demander dans quelle mesure l'augmentation du nombre de brevets s'est accompagnée d'avancées techniques concrètes. Les chapitres suivants sont consacrés à cette question. Plus précisément, ils se concentrent sur les fabricants d'éoliennes pour apprécier la corrélation entre le nombre de brevets détenus par les entreprises et leurs contributions au progrès technique. L'objectif est double. Premièrement, il s'agit de mieux comprendre si le système des brevets permet de tels changements. Deuxièmement, il s'agit d'informer sur la pertinence du recours au brevet comme témoin du progrès technique.

Le chapitre 2 est consacré à la distinction entre innovation de produit et l'innovation de procédé sur la base d'informations fournies par les brevets. La littérature théorique distingue depuis longtemps ces deux éléments : l'innovation de produit est censée se traduire par des améliorations dans les caractéristiques techniques des biens tandis que l'innovation de procédé affecte le coût de ces biens. Après avoir récupéré la description complète des brevets liés à la technologie éolienne déposés à l'OEB, nous utilisons des techniques d'analyse sémantique pour mesurer le caractère produit et procédé des brevets (*productness* et *processness*, respectivement). Nous nous appuyons sur le travail de [Banholzer et al. \(2019\)](#), qui identifient des mots-clés propres aux produits et aux procédés pour permettre une telle distinction. Cependant, à leur différence, nous considérons qu'un même brevet peut couvrir à la fois une innovation de produit et une innovation de procédé.³⁰ Le caractère produit (resp. procédé) d'un brevet est donné par le nombre d'occurrences de mots-clés de produit (procédé) dans le document associé par rapport à la fréquence totale des mots-clés (produit et procédé). Une analyse descriptive de la dynamique de ces indicateurs entre 1990 et 2017 met en évidence le fait que, jusqu'au milieu des années 2000, l'innovation (brevetée) était principalement axée sur le produit. Si l'innovation de produit reste dominante par la suite, la période 2004-2005 représente une rupture dans l'orientation de l'innovation, l'innovation de procédé commençant à gagner du terrain à partir de ce moment-là. Une explication possible de ce phénomène est liée au type de soutien public apporté à la technologie éolienne. Nous soutenons que la promotion de l'énergie éolienne par le biais d'un tarif d'achat garanti (d'une tarification du CO₂) est susceptible d'orienter l'innovation vers l'innovation

³⁰Par exemple, en 1880, Joseph Swan a obtenu un brevet pour un procédé de fabrication d'ampoules à incandescence qui permettait d'éviter leur noircissement précoce.

de procédé (produit). Cela provient du fait que dans le cadre d'une politique de tarification du CO₂, le prix de vente de l'énergie dépend directement de la demande alors que ce n'est pas le cas dans le cadre d'un soutien de type tarif d'achat garanti (TAG). Dans un modèle simple, dans lequel une faible vitesse de vent est associée à une forte demande d'électricité et inversement, les développeurs de parcs éoliens soumis à une tarification CO₂ seront intéressés par des turbines performantes à faible vitesse de vent, à laquelle le prix de l'électricité est le plus élevé, ce qui peut être atteint par l'innovation de produit. En revanche, dans le cadre d'une politique de type TAG, ils devraient accorder moins d'attention au volume de production et être encouragés à choisir des machines moins chères, l'innovation de procédé étant ici la clé. L'observation de l'évolution des montants des TAG en Europe et du prix du carbone du système européen d'échange de quotas d'émission va dans ce sens. La distinction entre innovation de produit et innovation de procédé, et notamment les mesures du caractère produit et procédé des brevets, seront mobilisées dans les deux chapitres suivants.

Le chapitre 3 vise à confronter les décomptes de brevets à des mesures objectives (ou du moins indépendantes des brevets) du progrès technique et partage ainsi un objectif commun avec les travaux de [Trajtenberg \(1990\)](#). Les fabricants d'éoliennes et les informations techniques concernant leurs machines sont issus de la base de données THEWINDPOWER. L'innovation de produit est considérée comme influant sur la production d'électricité des turbines, qui dépend de la vitesse du vent, du diamètre du rotor et de ce qu'on appelle le *coefficient de puissance*. On considère que les fabricants ne peuvent agir que sur ces deux derniers éléments, c'est-à-dire que l'innovation conduit à une augmentation de la production d'électricité des turbines par deux canaux : l'augmentation (i) de la taille du rotor pour capter plus d'énergie du vent, et/ou (ii) du coefficient de puissance qui reflète l'efficacité de la conversion de l'énergie cinétique en énergie électrique. Si l'augmentation de la hauteur de la turbine peut permettre d'atteindre une vitesse de vent plus élevée, notre objectif ici est de comparer les performances des turbines dans des conditions de vitesse de vent communes. Le coefficient de puissance dépend de la forme de la courbe de puissance de l'éolienne et est calculé à vitesse de vent donnée. Puisque nous souhaitons observer un niveau de performance global, nous nous basons sur la production annuelle d'énergie (AEP) espérée de chaque turbine, dont le calcul est basé sur une distribution des vitesses de vent de Rayleigh associée à la courbe de puissance de chaque turbine. Enfin, le rapport entre l'AEP espérée et la taille du rotor fournit une indication sur l'efficacité globale du processus de conversion pour chaque turbine. Cet indicateur sera appelé la performance des turbines. Nous utilisons ensuite des techniques d'analyse des frontières pour représenter l'état de l'art à une période donnée. Plus précisément, une turbine se situe à la frontière si elle permet d'atteindre le

niveau de performance le plus élevé pour une taille de rotor donnée. Il est donc implicitement considéré qu'il est difficile d'améliorer la taille sans sacrifier la performance, ce qui apparaît de manière assez frappante dans nos données. Nous évaluons les contributions respectives des fabricants de turbines au progrès technique en appréciant la localisation des turbines investissant le marché à l'année t par rapport à la frontière en $t - 1$. Un fabricant est considéré comme ayant contribué au progrès technique à l'année t si l'une de ses turbines sortie en t se situe au-dessus de la frontière en $t - 1$. L'étendue de cette contribution est mesurée sur la base de distances radiales. Enfin, nous vérifions la relation entre le nombre de brevets et les contributions des entreprises au progrès technique à partir d'un panel de fabricants de turbines sur la période 2000-2017. Nos résultats suggèrent qu'au début de la période, des améliorations ont été possibles malgré un faible nombre de brevets dans le secteur. Cependant, nous observons par la suite que les entreprises ayant des contributions au progrès technique sont principalement celles qui détiennent des brevets. Pour réduire l'effet de la dynamique dans le recours global au brevet, nous comparons les contributions des entreprises à la part de brevets qu'elles détiennent parmi l'ensemble des brevets du secteur. Nous observons une corrélation positive et significative entre une version décalée de cet indicateur et les contributions des entreprises au progrès technique. Le délai pour nécessaire à une invention pour atteindre le marché est d'environ quatre ans. En outre, nous soulignons la nécessité de prendre en compte la taille du portefeuille de brevets (c'est-à-dire le nombre de brevets actifs à une période donnée) plutôt que les dépôts de brevets lorsque l'on s'attache à évaluer le progrès technique à l'aide de données de brevets. Enfin, la mesure du caractère produit des brevets semble utile pour appréhender les contributions des entreprises au progrès technique.

Le chapitre 4 inclut la dimension procédé à l'analyse. Dans la même veine que le précédent chapitre, l'idée est d'évaluer la nature de la relation entre décomptes de brevets et innovation de procédé. Dans le cas de l'énergie éolienne, ce que l'on devrait attendre de l'innovation de procédé est une diminution dans le coût des turbines, qui affecte directement le coût d'investissement de la mise en service des parcs. Le coût des turbines est le prix facturé aux développeurs de parcs éoliens, qui n'est pas directement observé. À partir des informations sur le choix effectif d'un modèle particulier d'éolienne par les développeurs de parcs éoliens en Europe, fournies par la base de données THEWINDPOWER, nous estimons un modèle de profit aléatoire basé sur le modèle d'utilité aléatoire de [McFadden \(1974\)](#). En effet, contrairement aux consommateurs qui choisissent l'alternative qui leur procure la plus grande utilité, les développeurs de parcs éoliens choisiront l'éolienne qui maximise leur profit espéré. La partie positive du profit provient de la vente de la production d'électricité sur le marché national, tandis que la partie négative comprend les coûts d'exploitation et

de maintenance ainsi que les coûts d'investissement. [Sarja and Halonen \(2013\)](#) ont mis en évidence, à partir d'une enquête menée auprès d'énergéticiens finlandais, les principaux facteurs influençant le choix d'un modèle de turbine. Ces derniers comprennent le volume de production et les facteurs de coût ainsi que d'autres facteurs (pour la plupart non observés) tels que la fiabilité ou la disponibilité. Dans un modèle très simple, nous modélisons le choix d'une éolienne comme une fonction de la production d'énergie des turbines ainsi que de certaines autres caractéristiques des turbines telles que la taille et la puissance nominale. La production énergétique attendue de chaque turbine pour chaque parc éolien est calculée avec précision en tenant compte de la vitesse moyenne réelle du vent à l'emplacement du parc. Comme nous n'observons que la partie positive du bénéfice, la partie non observable du bénéfice, c'est-à-dire non expliquée par les différences de caractéristiques techniques, peut refléter des différences dans le prix facturé par les fabricants ainsi que dans des caractéristiques non observables telles que les facteurs de fiabilité ou de disponibilité affectant le coût. L'introduction de variables indicatrices d'année permet d'estimer l'effet du temps sur la probabilité de choisir un fabricant spécifique. La confrontation de ces estimations avec le nombre de brevets de procédé indique que ces différences peuvent être dues à des différences de prix. En effet, l'évolution de la part des brevets de procédé détenus par les fabricants coïncide dans une certaine mesure avec l'évolution dans l'effet des inobservables. Ceci suggère qu'en investissant dans l'innovation de procédé, les entreprises sont capables de gagner des parts de marché en diminuant le prix de leurs machines. Les données sur les brevets, lorsqu'elles tiennent compte de leur caractère « procédé », semblent donc capturer la dynamique de l'innovation de procédé.

Cette thèse délivre finalement un message encourageant au regard du système européen des brevets. En effet, en nous concentrant sur l'industrie européenne de l'énergie éolienne, nous montrons que les usages stratégiques des brevets ne sont pas généralisés et que la procédure d'opposition est principalement utilisée dans son objectif initial d'éliminer les brevets indus. Nous mettons également en évidence une relation positive entre brevets et progrès technique au niveau des entreprises. En particulier, l'évolution dans la capacité des firmes à repousser la frontière technologique, qui est utilisée pour refléter l'innovation de produit, coïncide avec l'évolution de la taille du portefeuille de brevets des entreprises. De plus, concernant l'innovation de procédé, le nombre de brevets de procédé détenus par les entreprises semble refléter les différences dans les parts de marché des entreprises, ce qui suggère que ces dernières peuvent être expliquées par des différences dans les prix pratiqués par les fabricants. Cependant, si les décomptes de brevets peuvent être utilisés pour refléter l'innovation, leur usage appelle à une certaine prudence. Nous soulignons notamment l'importance de considérer les portefeuilles de brevets plutôt que les décomptes

simples des dépôts de brevets, ainsi que de tenir compte du délai de mise sur le marché des innovations. Mis bout à bout, ces éléments suggèrent que, sur la base d'un focus sur l'industrie de l'énergie éolienne, rien ne prouve que le système européen des brevets ne remplit pas sa fonction de moteur de l'innovation. Par conséquent, la promotion de technologies respectueuses de l'environnement par le biais d'un système de brevets dédié demeure une option valable.

* * *