Research & development towards green technologies under technical and policy uncertainty: A real options approach to investments

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0. Populärwissenschaftliche Einführung in das Thema

Osymandias
Percy Bysshe Shelley, Übersetzung von Adolf Strodtmann[1]

Ein Wanderer kam aus einem alten Land,
Und sprach: Ein riesig Trümmerbild von Stein
Steht in der Wüste, rumpflos Bein an Bein,
Das Haupt daneben, halb verdeckt von Sand.

Der Züge Trotz belehrt uns: wohl verstand
Der Bildner, jenes eitlen Hohnes Schein
Zu lesen, der in todten Stoff hinein
Geprägt den Stempel seiner ehrnen Hand.

Und auf dem Sockel steht die Schrift: „Mein Name
Ist Osymandias, aller Kön'ge König: -
Seht meine Werke, Mächt'ge, und erbebt!“

Nichts weiter blieb. Ein Bild von düstrem Grame,
Dehnt um die Trümmer endlos, kahl, eintönig
Die Wüste sich, die den Koloss begräbt.

Von der Weisheit des Sandes

Kopflos steht der großmächtige Pharao in der Wüste und sein Reich ist seit mehr als 3000 Jahren Geschichte. Kopflos stürmen wir hinterher, leisten Landverödung und Waldsterben Vorschub. Ein Drittel des Festlandes, so lautet eine neue Schätzung, wird bis zum Ende des Jahrhunderts versanden[2]. Sahara, Gobi, Kalahari, die Große Sandwüste Australiens - Trockengebiete und menschengemachte Ödlande dehnen sich immer weiter aus. Der Aralsee, einst der viertgrößte See der Welt, besteht nur mehr aus drei Tümpeln und schickt giftige Salzstürme aus. Abholzung, Überweidung und Übernutzung des Bodens, falsche Bewässerung sowie Techniken und politische Entscheidungen, die keine Rücksicht auf empfindliche Ökosysteme nehmen, sind Ursachen für die Degradation der Landschaft.

[1] Adolf Strodtmann: *Bibliothek ausländischer Klassiker in deutscher Übertragung*, 29. Band, Englische Literatur, Shellens ausgewählte Dichtungen, Erster Teil, Verlag des Bibliographischen Instituts, Hildburghausen (1866). Anmerkung: Osymandias ist der griechische Name von Ramses II.

[2] Siehe z.B. A. Newton: *Expanding sands*, Nature Reports Climate Change, abgerufen am 27. August 2009, doi:10.1038/climate.2009.84.

Genährt und beschleunigt werden diese Entwicklungen durch den Konsumhunger derer, die nicht darauf angewiesen sind, den ausgemergelten Böden ihren Lebensunterhalt abzutrotzen.

Änderungen in der Bodenbedeckung gehören neben Treibhausgasen, Aerosolen und Veränderungen der Sonneneinstrahlung zu den bestimmenden Einflussfaktoren der globalen Erwärmung. Zwischen 1.8°C und 4°C wird laut Weltklimarat die Temperatur bis Ende des Jahrhunderts im Vergleich zum letzten ansteigen[3]. Eine Erwärmung über 1.5°C hinaus setzt unumkehrbare Prozesse in Gang. Der Weltklimarat schätzt, dass dann etwa 20-30% der im Modell berücksichtigten Pflanzen- und Tierarten aussterben werden, sogar bis zu 70%, wenn die Temperatur um mehr als 3.5°C ansteigt. Das betrifft vor allem empfindliche Lebenswelten wie Korallenriffe, Regen- und Mangrovenwälder, aber auch Polareis, Gletscher und Tundra könnten völlig von der Landkarte verschwinden. Etliche Inseln und Küstenstreifen werden im Meer versinken, in anderen Regionen werden extreme Wetterschwankungen das Leben auf den Kopf stellen. Die Konsequenzen für die Weltbevölkerung, die bis zum Jahr 2050 auf etwa 9 Milliarden anwachsen wird, sind katastrophal - eine Verschärfung der ohnehin vorhandenen globalen Probleme wie Hunger, Armut und Krieg sind die Folge.

Können grüne Technologien den Klimawandel mildern?

Der Sand rinnt durch das Stundenglas. Es geht nicht mehr darum, einen Temperaturanstieg zu verhindern, sondern ihn zu beschränken. Im Strategiespiel „Civilization“ ist das einfach: man klettert höher im Technologiebaum und erfindet z.B. die Technik „Ökologie“ oder „Kernfusion“, das ermöglicht Umweltschutz, Kreislaufwirtschaft und stillt den wachsenden Energiebedarf. Der Weltklimarat zeigt in seinem Bericht kurz- und langfristige Möglichkeiten auf, wie sich die Menschheit dem Klimawandel anpassen und wie dieser gebremst werden kann - dem technologischen Wandel kommt dabei eine Schlüsselrolle zu. Dazu gehören nicht nur neues technisches Wissen und verbesserte Organisation, sondern auch fortschreitende Umweltkompetenz und gesellschaftliche Reife. Was nützt das energieautarke Ökohotel an der Ostsee, wenn Urlauber dort Zwischenstation auf ihrem Spaßflug um den Globus machen? Auf die Bilanz kommt es an, zum Beispiel gemessen am eigenen ökologischen Fußabdruck[4], und auf die Summe aller Mittel.

Verbesserte oder neue Technologien können die Anreicherung von Treibhausgasen in der Atmosphäre verringern. Die Internationale Energiebehörde beziffert zum Beispiel das Einsparpotential von nicht-fossilen Energiequellen und Effizienzsteigerungen auf fast 15 Gigatonnen Kohlendioxid bis zum Jahr 2030, wodurch der Temperaturanstieg auf 2°C begrenzt werden könnte. Den Löwenanteil von 80 % könnten Energieeffizienz und erneuerbare Energien sowie Biokraftstoffe übernehmen, den Rest erbrächten die Speicherung von Kohlendioxid und die Nutzung der Kernenergie (siehe Abb. 0.1)[5]. Dabei zählen Spei-

[3] Informationen aus dem 4. Sachstandsbericht des Zwischenstaatlichen Ausschusses für Klimaveränderungen der Vereinten Nationen, Ref. IPCC (2007). Die Spannweite für den optimistischen Anstieg ist 1.1°C-2.9°C, für den pessimistischen 2.4°C-6.4°C.

[4] Zum Weiterlesen: www.footprintnetwork.org .

[5] Szenario-Schätzung der Internationalen Energiebehörde, Referenz IEA (2009) im Literaturverzeichnis.

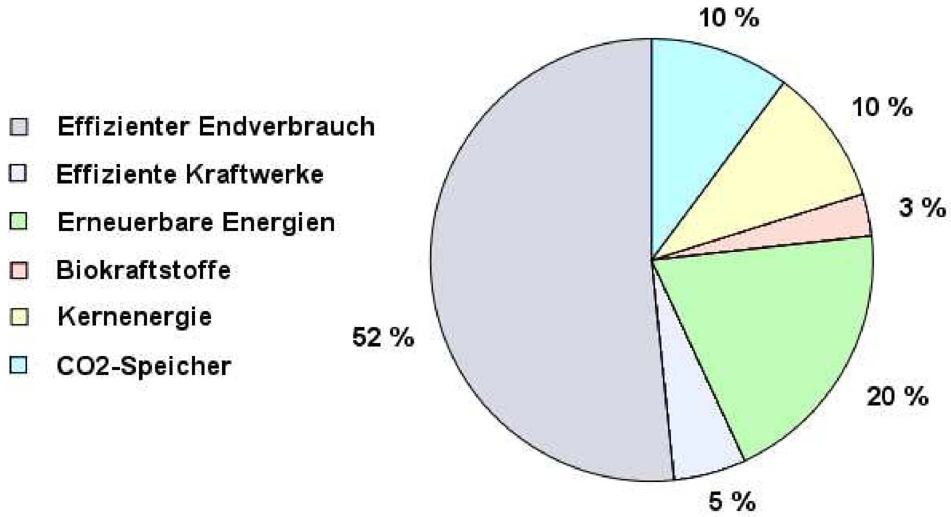


Abbildung 0.1.: Werden bis 2030 etwa 15 Gigatonnen Kohlendioxid gespart, kann der Temperaturanstieg auf 2°C begrenzt werden, beziffert die Internationale Energiebehörde.

chertechnologien im Gegensatz zur Kernenergietechnik zu den Umwelttechnologien - auch wenn es besser wäre, Schadstoffe zu vermeiden, als sie nachträglich beseitigen zu müssen.

Umwelttechnologien können neben der Klimabilanz des Energiesektors auch die anderer Wirtschaftsbereiche verbessern. Beispiele sind Techniken zur Wassergewinnung und -aufbereitung, Agrartechnologien, Aufforstung und Begrünung, geschlossene Stoffkreisläufe in der Industrie oder die Entwicklung von Materialien, die energieintensive oder umweltschädigende Produkte ersetzen können. Insgesamt schätzt der Weltklimarat, dass die Einsparsumme aus allen Technologien den Ausstoß von Treibhausgasen auf dem Niveau des Jahres 2000 stabilisieren könnte. Doch um dieses Potential auszuschöpfen, muss in Forschung und Entwicklung investiert werden. In die Verbesserung der Energieeffizienz und in die Erforschung nicht-fossiler Energiequellen müssten zum Beispiel etwa 12 Billionen US-Dollar innerhalb der nächsten 20 Jahre fließen - das ist ungefähr das Hundertfache des EU-Jahresetats (Quelle: Internationale Energiebehörde, IEA (2009)).

Ein unsicheres Geschäft mit vielen Optionen

Wissenschaftler und Politiker wagen einen weiten Blick in die Zukunft. Wird die Gesamtheit aller Tüftler und Unternehmer diese Summe aufbringen wollen und können? Was sind die Antriebsfedern und wie wird über eine Investition entschieden, wenn nicht klar ist, ob die Idee auch fruchtet? Die Daumenregel lautet: Springt mehr heraus, als investiert wird, lohnt sich der Plan und Geldgeber könnten überzeugt werden. Die Unternehmensberatung Berger schätzt, dass das Marktinteresse an Umwelttechnologien weiter stark wachsen wird. Innerhalb der nächsten zehn Jahre wird sich ihr Handelsanteil mehr

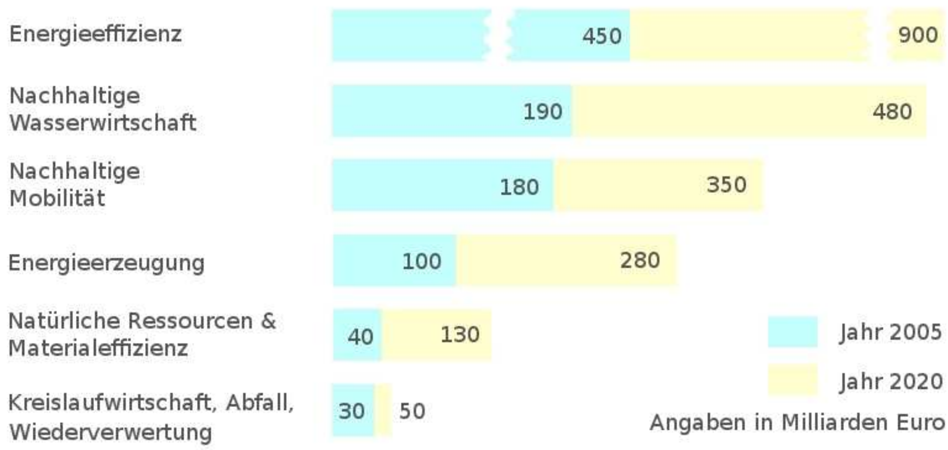


Abbildung 0.2.: Geschätzter Marktanteil von Umwelttechnologien aus der Sicht von Unternehmen im Jahr 2020 in Milliarden Euro. Quelle: RBSC (2007).

als verdoppeln und etwa 2200 Milliarden Euro betragen (siehe Abb. 0.2). Das gilt für alle Sektoren angefangen von Energieeffizienz, nachhaltiger Wasserwirtschaft, nachhaltiger Mobilität, Energieerzeugung, natürlichen Rohstoffen und Materialeffizienz bis hin zu Kreislaufwirtschaft, Abfall und Wiederverwertung.

Die Aussichten sind gut, doch die Schwierigkeit für Unternehmen besteht darin, abzuschätzen, wieviel investiert werden muss und was die eigene Erfindung oder Weiterentwicklung einmal Wert sein wird. Forschung und Entwicklung ist ein unsicheres und komplexes Geschäft, das sich über Jahre hinweg ziehen kann und bei dem der Zufall kräftig mitmischt. „Technischer Fortschritt“, so die Ökonomin Joan Robinson (1903-1983), „ist vorgegeben durch Gott, Wissenschaftler und Ingenieure“.[6] Da kann man sich kaum auf Papier und Bleistift verlassen, um das Vorhaben zu bewerten. Denn unter Umständen scheitert die Investition und ein guter Teil des Geldes, nicht selten Millionen Euro, versackt im Sand. Ein Beispiel für eine solche irreversible Investition sind Wissenschaftler und Techniker, die sich einen neuen Arbeitgeber suchen. Ihr Wissen und ihre Erfahrung sind für den Unternehmer verloren. Die Unsicherheit über Erfolg oder Misserfolg eines Projektes führt daher zu einem Risikoabschlag, wenn potentielle Investitionen geprüft werden. Allerdings überschätzen klassische Bewertungsmethoden dieses Risiko, denn sie klammern Handlungsspielräume aus, die sich vor allem in langfristigen Projekten mit Irreversibilität und hoher Unsicherheit eröffnen.

Eine alternative Bewertungsmethode ist die stochastische Optimierung. Sie liefert ein Mittel an die Hand, aus einer Palette von Handlungsmöglichkeiten die bestmögliche auszuwählen. Mit Unsicherheit behaftete Größen werden dabei mit Hilfe einer Wahrscheinlichkeitsverteilung berücksichtigt, die aus der Erfahrung gewonnen werden kann. Zum Beispiel ist zu entscheiden, ob mit voller Kraft oder zweckmäßiger auf Sparflam-

[6] Gefunden auf Seite 151 in Dosi (2000).

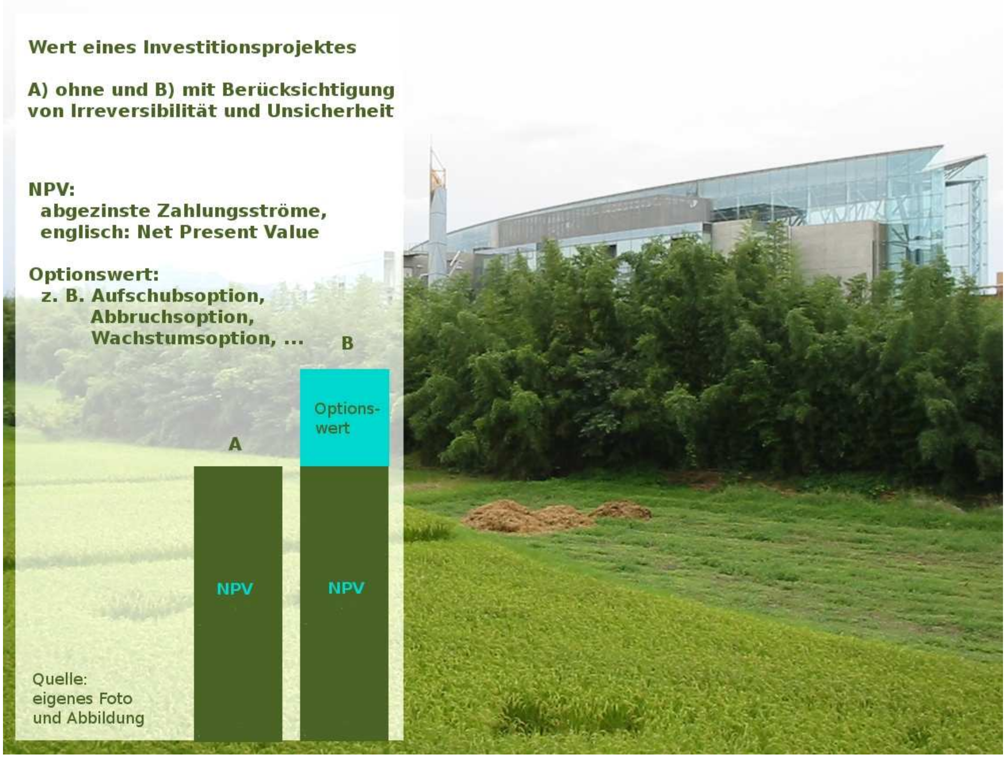


Abbildung 0.3.: Wert eines Investitionsprojektes A) ohne und B) mit Berücksichtigung von Irreversibilität und Unsicherheit.

me gekocht werden soll, ob der Beginn verschoben, das Projekt abgebrochen oder der eingeschlagene Kurs noch einmal überdacht werden soll. Viele dieser Optionen bestehen während der gesamten Umsetzung und können daher jederzeit in Frage kommen - zumal Wissen und Erfahrung wachsen, die Unsicherheit dagegen über den weiteren Verlauf abnimmt. In jedem Zeitpunkt wird dann für jede der Möglichkeiten gefragt, was wäre wenn? So gerät die Wahl des optimalen Entscheidungspfades zur mathematischen Herausforderung, doch die Fleißarbeit kann ein Rechnerprogramm übernehmen.

Ein Ergebnis der stochastischen Optimierung ist, dass Handlungsspielräumen ein Geldwert, der sogenannten Optionswert, beigemessen werden muss. Um diesen Betrag unterschätzen klassische Methoden, wie die Methode der abgezinsten Zahlungsströme, Investitionsprojekte (siehe Abb. 0.3). Der Fehler ist umso größer, je mehr das Vorhaben durch Irreversibilität und Unsicherheit geprägt ist. Aber genau das sind wichtige Kennzeichen von Forschung und Entwicklung. Dass Handlungspielräume bei der Bewertung meist unter den Tisch fallen, ist ein Grund dafür, dass zu zögerlich investiert wird.

Eine weitere Investitionsschwelle entsteht, weil Wissen auf Andere überschwappt und diese nutznießen können, ohne zu bezahlen. Patente schützen davor nur ungenügend - die Erfindung kann zum Beispiel imitiert werden. Das kann dazu führen, dass ein Unternehmen beschließt, die Entwicklung zunächst einmal abzuwarten. Denn Wissen ist Kapital, und das soll zu allererst für das eigene Unternehmen arbeiten. Stünde andererseits alles Wissen frei zur Verfügung, könnte auch manchen Irrtümern aus dem Weg gegangen und nicht jedes Rad müsste zweimal erfunden werden. Solche Effekte außerhalb des eigenen Einflusses bewirken, dass insgesamt etwa zwei- bis viermal weniger in Forschung und Entwicklung sowie den Erwerb von neuen Technologien investiert wird, als es klassische Modelle erwarten lassen.[7]

Was hat Umweltpolitik mit Forschung und Entwicklung zu tun?

Umweltfreundlicher technischer Fortschritt bleibt im Vergleich noch mehr unter seinem Potenzial. Denn es kommt hinzu, dass Umweltverschmutzung und Umweltverbrauch für Unternehmen und Konsumenten kaum etwas kosten. Diese Kosten werden der Gesellschaft aufgebürdet. So besteht wenig geldwerter Anreiz, ökologisch und nachhaltig zu wirtschaften - oder zu erfinden. Zum Beispiel effizienter mit Energie umzugehen. Durchschnittlich 3.5 Eurocent kostet es, den Energiebedarf für eine Stunde Strom herzustellen. 6-8 Eurocent müssten pro Kilowattstunde bei Kohle, Erdöl und Erdgas draufgeschlagen werden, würden die Kosten für Luftverschmutzung und Klimawandel eingerechnet. Mit knapp einem Eurocent an nicht berücksichtigten Kosten für die Allgemeinheit schneiden Wind, Wasser und Sonne schon besser ab (Quelle: BMU- Gutachten 2007, Krewitt and Schlomann (2007)). Doch ohne staatliche Unterstützung wie Ökosteuer oder dem Erneuerbare Energien-Gesetz, das Preise und Abkaufsicherheit garantiert, wären diese Alternativen nicht wettbewerbsfähig.

Viele Unsicherheiten, zögerliche Investoren, überschwappendes Wissen, Umweltverbrauch unter Wert - ist es also realistisch, dass die notwendigen 12 Billionen US-Dollar innerhalb der nächsten 20 Jahre rollen werden, um mittels grüner Technologien den Klimawandel zu verlangsamen? Es ist nicht realistisch, falls nicht Barrieren abgebaut und Umweltpolitik ausgebaut würde, wirft der Weltklimarat ein. Also ist Umweltpolitik gefragt, den technischen Fortschritt anzukurbeln und den Weg in die richtige Richtung zu ebnen. Das Portfolio an Politiken ist vielseitig: Subventionen für Umweltforschung, Steuern und Abgaben, handelbare Emissionszertifikate, dynamische Standards für Energieeffizienz, verschärftes Haftungs- und Umweltrecht oder grüne Beschaffung durch die öffentliche Hand sind nur ein paar Beispiele.

Da stellt sich die Frage, was ist effizient? Präziser, was ist öko-effizient? Idealerweise müssten Umweltpolitiker wissen, was in den Köpfen von Erfindern vorgeht, um einschätzen zu können, welche der Technologien nicht nur viel verspricht. Sie müssen sogar abschätzen, welche Auswirkungen Politikmaßnahmen und Technologien haben *werden*. Wird der Energieverbrauch tatsächlich sinken oder tappt man in Jevons Falle, d.h. es wird zwar effizienter produziert, aber in der Summe mehr verbraucht? Aufwand und Nutzen müssen im Verhältnis stehen. Auch hier spielen Unsicherheiten eine wichtige Rolle, denn ein Klima wandelt sich nicht von heute auf morgen, weder in die eine noch in die andere Richtung. Auf welche Weise kann Umweltpolitik Unternehmen mobilisieren, umweltfreundliche Technologien zu erforschen, wenn unsicher ist, wann und ob ein

[7] Quelle: Gillingham et al. (2009)

Durchbruch erreicht werden kann? Welche Handlungsspielräume hat ein Unternehmen, wenn Subventionen, Steueranreize oder Effizienzstandards unerwartet wegfallen oder geändert werden? Technologische Unsicherheit und Politikunsicherheit - das sind die beiden Brillengläser, mit denen in dieser Arbeit die Investitionsentscheidungen eines einzelnen Unternehmens studiert werden, um Antworten auf die aufgeworfenen Fragen zu finden. Stochastische Optimierung (Theorie der Realoptionen) kommt zum Einsatz, um zum Beispiel auszuloten, ob sich die Investition in Rostocks Meereswindpark lohnt oder wie Energieeffizienzforschung beflügelt werden kann.

Das sind nur Mosaiksteinchen im Verständnis darüber, wie das Potenzial grüner Technologien ausgeschöpft werden kann, um den Klimawandel zu mildern. In der Tat wird jedes aus Mosaiksteinchen geformte Bild nur ein unvollständiges Abbild der Wirklichkeit bleiben. Ein vollständiges Bild zu schaffen, hieße, Vergangenheit und Zukunft genau zu kennen. Das bringt uns zurück an den Ausgang dieser Einführung. Da immer Aspekte der Vergangenheit im Dunkel bleiben werden, wird ein Historiker nicht perfekt rekonstruieren können, was zum Untergang von Osymandias' Reich führte. Genauso wenig wird ein Künstler die verwitterte Statue des legendären Pharao detailgetreu wiederherstellen können. Und ebenso wenig ist Wissenschaft in der Lage, einen präzisen Weg in die Zukunft zu beschreiben. Eine interessante Überlegung findet sich da im Roman von Antoine de Saint-Exupéry. Die Hauptfigur dieses Buches, der Prinz eines Wüstenstaates, unterhält sich auf langen Spaziergängen mit seinem Vater über die Verantwortung, die das Fällen von Entscheidungen mit sich bringt. Eines Tages sagt der Sohn: *Immer geht es nur darum, die Gegenwart zu ordnen. Was fruchtet es, über ihre Erbschaft zu streiten? Die Zukunft soll man nicht voraussehen wollen, sondern möglich machen.*[8] In diesem Sinne soll die Arbeit dazu beitragen, besser zu verstehen, wie es dazu kommen kann, dass Fehlentscheidungen getroffen werden und wie diese verhindert werden können. Es ist von Wert, Handlungsspielräume offen zu halten, lautet ein zentrales Paradigma der Theorie der Realoptionen.

[8] Antoine de Saint-Exupéry: *Die Stadt in der Wüste*, S. 187, Ullstein Buchverlage, Berlin (1997).

1. Introduction

1.1. Motivation

Ozymandias
Percy Bysshe Shelley[1]

I met a traveller from an antique land,
Who said - "two vast and trunkless legs of stone
Stand in the desert ... near them, on the sand,
Half sunk a shattered visage lies, whose frown,
And wrinkled lips, and sneer of cold command,
Tell that its sculptor well those passions read
Which yet survive, stamped on these lifeless things,
The hand that mocked them, and the heart that fed;
And on the pedestal, this legend clear:
My name is Ozymandias, King of Kings,
Look on my Works ye Mighty, and despair!
Nothing beside remains. Round the decay
Of that colossal Wreck, boundless and bare
The lone and level sands stretch far away."

The wisdom of the sands

The mighty pharaoh stands headless in the desert and his kingdom is history for more than 3000 years. Mindlessly we are storming the earth, pushing the land to become desolate and causing forests to die. One third of the continents, according to recent estimate, will turn into sand by the end of this century[2]. Sahara, Gobi, Kalahari, the Great Sandy Desert of Australia - drylands and man-made wastelands are expanding. Lake Aral, once the fourth largest in the world, today barely three ponds, sends poisonous sand storms towards villages and cities. Deforestation, overgrazing, soil over-use, wrong irrigation, as well as techniques and political decisions that do not take our sensitive eco-systems into consideration are reasons for the degradation of our landscape.

Canopy changes, along with green house gases, aerosols, and changes in solar irradiation, are among the main factors that cause global warming. The global temperature will rise, in comparison to its value at the end of the last century, between 1.8 °C and 4 ° C by

[1] Percy Bysshe Shelley: *Ozymandias*, MS Shelley e. 4 fol. 85 r, Bodleian, Library, University of Oxford (1817-1818).

[2] See e.g. A. Newton: *Expanding Sands*, Nature Reports Climate Change, Published online: 27 August 2009, doi:10.1038/climate.2009.84.

the end of this century according to the International Panel of Climate Change (IPCC)[3]. An increase above 1.5 °C will trigger irreversible processes resulting in the death of 20 to 30 % of all the plants and animals considered in their model. If the temperature were to increase by more than 3.5 °C, an alarming 70 % of species would become extinct. This affects especially sensitive eco-systems such as coral reefs, rainforests and mangrove forests, but also polar ice, glaciers, and tundra could completely disappear from the map. Many islands and coastal areas would sink into the ocean. In other regions extreme weather conditions would turn normal life upside down. Consequences for humankind, at a projected population of 9 billion people by the end of 2050, are catastrophic - intensifying life-threatening global problems such as famine, poverty, and war.

Can green technologies alleviate climate change?

The sand is running through the hourglass. It is not about avoiding a temperature rise, but limiting it. In the strategy game 'Civilization' this is simple: the player climbs the tree of technologies and invents techniques like 'ecology' or 'fusion' enabling environmental protection and closed-loop industrial production. Even the growing hunger for energy can be reduced. In its report, the IPCC suggests how we could adapt to and slow down climate change in the short and long term. Technological change plays a key role. Improved or new technologies allow lowering the accumulation of green house gases in the atmosphere. According to the International Energy Agency, for example, non-fossil energy sources and efficiency improvements have the potential to prevent the release of as much as 15 gigatons of carbon dioxide by 2030 (IEA, 2009). This could limit the increase in temperature to 2 °C. The lion's share, 80 %, could be shouldered by energy efficiency, renewable energies, and biofuels. The remainder could be attained by capturing carbon and using nuclear energy. In order to tap the full potential, investments in research and development are needed. For example, in order to improve energy efficiency and to explore non-fossil energy sources. 12 trillion US Dollars are needed within the next 20 years. But the IPCC comments on the options to respond to climate change

> *"The capacity to adapt and mitigate is dependent on socio-economic and environmental circumstances and the availability of information and technology ..."*, and further on, *"... The economic mitigation potential, which is generally greater than the market mitigation potential, can only be achieved when adequate policies are in place and barriers are removed..."*, (IPCC, 2007, p. 56-58).

Thus, green technologies bear a strong potential to alleviate climate change, but their utilisation is contingent on interdependent factors which are by nature impossible to anticipate or predict. Yet, decisions about adaption and mitigation measures have to be made. A laissez-fair strategy is not an option. Therefore, a better understanding of the aspects of this complex problem is needed. This thesis explores how the decision to invest

[3] 4th Synthesis Report, IPCC (2007). The error margin for the best estimate in the optimistic scenario is 1.1 °C - 2.9 °C. For the pessimistic scenario it is 2.4 °C - 6.4 °C. Numbers are given for the years 2090-2099 relative to 1990-1999.

in research and development towards greener technologies is influenced by environmental policies in a world of technical and policy uncertainty.

1.2. Purpose and outline

Technical change can contribute to alleviating climate change, but this potential can only be realised if policies provide incentives for firms to invest in innovations stimulating the development or adoption of greener technologies. Relatively little is known about how to stimulate the phase of research and development, whereas the study of induced technology adoption and diffusion has received considerable attention in environmental-economics. This observation is the starting point for this thesis. On the basis of theoretical models, we will explore how policy can spur research and development (R&D) of environmental technologies. A key issue in the investigation is to incorporate uncertainty and irreversibility. But these features are most often missing in the literature. There are several dimensions of uncertainty. A generic uncertainty of R&D is related to the scientific progress of an R&D project. Therefore, apart from sunk investment cost, this thesis considers technical uncertainty. The second important uncertainty, which we will also include in the context of our research topic, is uncertainty about the policy framework. Our sequential investment models are solved by stochastic optimisation (real option analysis). In order to reduce the complexity of the research problem, we will focus on the investment decisions of a single firm.

The background to the analysis is provided in Chapter 2. In Section 2.1, we will discuss what is meant by 'green technological progress', and we will present empirical findings of its determinants. Section 2.2 continues with an outline of the rationale for policy interventions, illustrating environmental and knowledge-related externalities. Abstracting from uncertainties, principal options for environmental and technology policy are reviewed and then discussed with respect to their (dynamic) efficiency. In Section 2.3, we will introduce the concepts of irreversibility and uncertainty. We provide arguments as to why neglecting these features can be misleading. The environmental-economics literature that takes irreversibility and uncertainty into consideration is small, particularly where R&D investment is concerned. We will survey their findings on green technological progress, uncertainty, and environmental policy. Section 2.4 concludes the chapter by summarising open questions from the literature and implications for the design of theoretical models.

In the beginning of Chapter 3, we illustrate the formalisation of technical uncertainty and present the main findings from the literature on real options of R&D investments. Afterwards, different sequential investment models incorporating sunk investment costs and technical uncertainty are studied. In Section 3.3, we describe the basic model and discuss its solution and limitations. To solve the model, we use the methods of dynamic programming and Monte Carlo simulation. The basic model is then applied to offshore wind park investments in Section 3.4. We extend the basic model to study the impact of the German Renewable Energy Act on investment decisions. In Section 3.5, we develop a model to analyse the impact of environmental policy on a firm's decision to develop energy-saving technologies. Environmental policy takes the form of energy taxes, tradable and non-tradable energy quotas, as well as R&D investment subsidies. Section 3.6 summarises the chapter.

In Chapter 4, we introduce policy uncertainty. After a short discussion as to the importance of this extension in Section 4.1, Section 4.2 outlines the findings in R&D investment models that consider policy uncertainty. This is followed by a description of our way to formalise this type of uncertainty (Section 4.3). The model in Section 4.4 analyses the influence of uncertain R&D subsidies on the investment decisions. We study two cases. In the first one, it is uncertain how long subsidies will be available. In the second one, the launch of an R&D programme is not known. In Section 4.5, we explore the impact of uncertainty of energy taxes and quotas. The chapter is concluded by a summary.

Chapter 5 summarises the main results of this thesis and discusses potential starting points for future research.

2. Basic concepts and survey of literature

2.1. Green technological progress

Progress is commonly understood as a gradual betterment. Thus, green technological progress in principle describes technological innovation that benefits the environment. This leads to three questions. First, what are the characteristics of technological change? Second, what does 'benefiting the environment' mean, and how can this be measured? And third, what is the broader context green technological progress has to be placed in?

Technological progress passes three basic stages which are called invention, innovation, and diffusion (Schumpeter, 1942). At first, ideas are born which may lead to an invention. This can be a technical invention, i.e. a new process or a novel product, or an alternative way of organising the production cycle. The invention is tested and further developed. Some ideas ripen and are brought to the markets. This turns an invention into an innovation. Possibly, an innovation spreads among other users who further adapt it to their needs - the innovation enters the stage of diffusion[1]. Technological progress is, however, not a linear process but complex and subject to interruptions, corrections, and coincidences. Selected stylised facts of technical change are, for example, the 'intrinsically *uncertain* nature of inventive activity', the role of 'long-run planning for firms (and not only for them)', and 'a significant correlation between R&D efforts and an innovative output' (Dosi, 2000, p. 151).

In all three stages of the innovation process, the magnitude of change may be different. A common taxonomy is to distinguish between 1) incremental and 2) radical innovation, 3) new technology systems, and 4) changes of techno-economic paradigms (Freeman and Perez, 1988). Incremental innovations are continuous improvements of technologies or prototypes in use, often conceptualised as learning by doing (Arrow, 1962) or learning by using (Rosenberg, 1982). Radical innovations happen sporadically[2] and are typically results of mid- or long-term research and development activities of a single firm or a research network. Some of them, especially if technological and organisational innova-

[1] There are two stylised facts for the adoption of innovations. First, there is a lag between the availability of an innovation and its adoption. Second, the diffusion among applicants follows an S-curve. Innovators are the first few users followed by a growing number of early adopters. Possibly, the diffusion gains momentum until a majority has introduced the innovation. Afterwards, the diffusion process slows down again reaching market saturation (Rogers, 1995). For a review on the literature of timing of technology adoption, see Hoppe (2002). For a review of empirical literature see Vollebergh (2007).

[2] That is if viewed from outside of the innovator's institution. From inside, the learning process is to a large extend also of 'cumulative nature', see Dosi et al. (1994, stylised fact 25).

tions are combined, have the potential to induce broader structural changes affecting several sectors and establishing new technology systems. Even more far-reaching in the magnitude of change is the fourth type. For this type, a new technological regime dominates the development in most sectors and countries for decades, also able to shift the behaviour of societies.

Technological change is to a large extend driven by steered economic activities that promise profits.[3] The decision for these activities is influenced by various factors, e.g. the stock of already existing knowledge, relative cost of input factors, expected market demand, other market conditions such as the number of competitors, preferences of suppliers and consumers, as well as institutional, legal, and policy structures. The relevance of these factors is in flux during the innovation process. For example, supply-side factors seem more important for research and development activities, whereas the diffusion of innovation is likely stronger demand-side driven.[4]

Green technological progress drives the direction and rate of technological change towards 'environmental benefits'. This is subject to on-going discussions on how to define eco-innovations. We follow a recent definition stating

> *Eco-innovation is the production, application or exploitation of a good, service, production process, organisational structure, or management or business method that is novel to the firm or user and which results, throughout its life cycle, in a reduction of environmental risk, pollution, and the negative impacts of resources use (including energy use) compared to relevant alternatives* (Kemp and Pearson, 2008).

Note that it is the actual benefit for the environment and not the intention of the innovation that counts.[5] This implies on the one hand that conventional innovations, too, can fulfill the criteria, e.g. new, resource saving products, as long as they are 'doing better' than their alternatives. On the other hand, innovations with the attribute 'environmental' are not necessarily eco-innovations. This has important implications for empirical studies and the development of appropriate indicators. In order to assess whether an innovation performs environmentally benign, the innovation should be - ideally - subject to a life cycle assessment. A possibility would be to measure how eco-efficient an innovation is. This can be defined as a switch in the technology system through '... the

[3] See e.g. Ruttan (1997); Jaffe et al. (2003); Popp et al. (2009) for a comparison of the three major theories that build on this assumption. The neoclassical *induced innovation approach* splits into micro-economic investment models and macro-economic growth models (New Growth Theory). Both are rooted in General Equilibrium Theory. On the contrary, permanent system changes are the center of the *evolutionary approach*. It replaces maximising investment strategies with satisfying strategies through selection, imitation, and variation. The *path dependence approach* draws from the historical observation that dominant technologies determine development paths often leading to technological irreversibilities and persistencies.

[4] For an introduction to the literature on 'pushing' supply-side factors, 'pulling' demand-side factors, and policy push-and-pull for environmental innovations, see e.g. Horbach (2008); Rennings and Rammer (2009). See Rennings (2000) for a discussion from the point of view of ecological-economics.

[5] Accordingly, the stress of this definition is on the second and the third stage of green technological progress as the environmental impact of an invention has to be assessed and not its ambition or potential. For a discussion of this and the evolution of the definition see Kemp and Pearson (2008).

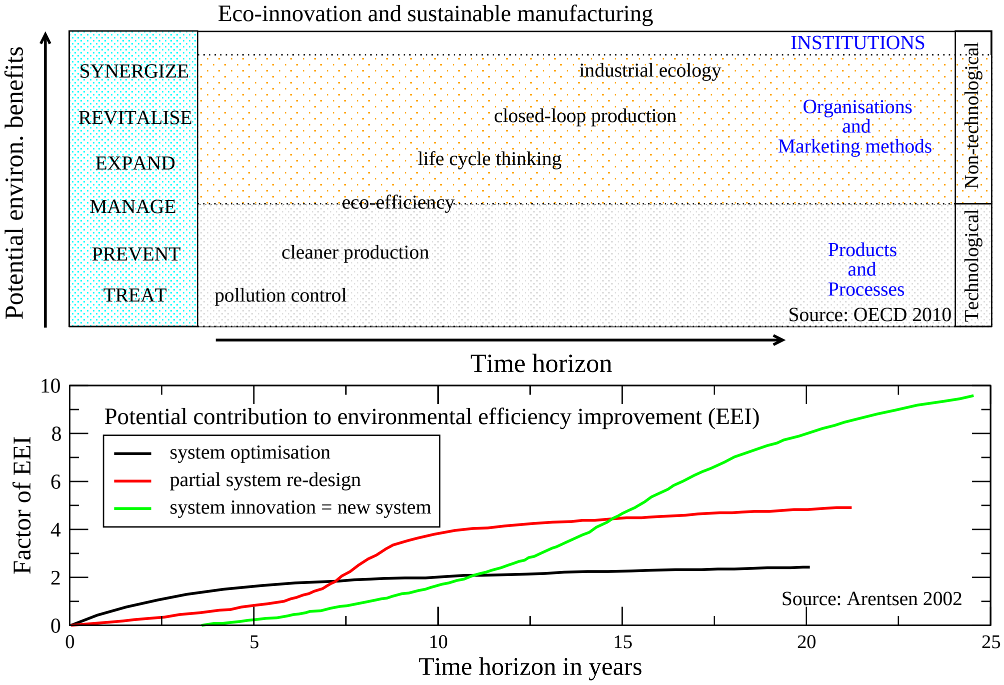


Figure 2.1.: Evolution of eco-innovations (upper part of figure) and estimates of the factor for environmental efficiency improvements (lower part).

delivery of competitively priced goods and services that satisfy human needs and bring quality of life while progressively reducing environmental impacts of goods and resource intensity throughout the entire life cycle to a level at least in line with the Earth's estimated carrying capacity ...' (WBCSD, 1996). Thus, eco-efficiency is operationalised as the ratio of the product or service value to its environmental impact. Suggestions of different aggregate and firm-level definitions of eco-efficiency are provided in Kemp and Pearson (2008).

Derived from the above definition, eco-innovations are classified into A) environmental technologies, e.g. green energy technologies, B) organisation innovation, e.g. environmental auditing, C) product and service innovation, e.g. eco-housing, carsharing, and D) green system innovations, e.g. renewables-based energy systems. Environmental technologies are further divided into pollution control technologies, cleaning-up technologies, waste management equipment, cleaner process technologies, environmental monitoring and instrumentation, noise and vibration control, water supply, and green energy technologies. Note that product changes are not included in the group of environmental technologies while they are in a categorisation of Hohmeyer and Koschel (1995)[6].

The magnitude of change an eco-innovation triggers relates to its potential to con-

[6]Hohmeyer and Koschel (1995) distinguish between integrated and additive environmental technologies. Integrated technologies affect inputs, the production process, or outputs. Additive technologies are 'attached' at the end of a production process and are therefore also called end-of-pipe technologies.

tribute to a sustainable development. The OECD recently published a strategy on how to enable industrial green growth (OECD, 2010). The upper part of Fig. 2.1 visualises this strategy showing the path for eco-innovations towards sustainable manufacturing. Technological as well as non-technological change are considered. Green technological change comprises 1) pollution control to 'treat' environmental contamination, 2) cleaner production technologies to reduce environmental burdens by substituting harmful substances or optimising resources and processes, and, 3) the concept of eco-efficiency for systematic environmental management and monitoring. Non-technological change includes, in addition, the extension to life cycle thinking (e.g. green supply chain management), the introduction of closed-loop production (e.g. disposable fabrics), and the development of an industrial ecology that is based on integrated systems of production. Non-technological change partially overlaps with the concept of eco-efficiency. Its potential impact is, however, bigger than that of technological change as it makes a development towards new technology systems more likely.

In addition to this evolutionary concept by OECD, the lower part of Fig. 2.1 shows the factor of improvement in environmental efficiency for different system innovations and their development along the time horizon. The magnitude of improvements has been estimated in research studies accompanying the Dutch Sustainable Development Programme (Arentsen et al., 2002). In the short- to medium-term, improvements are especially achievable through technical change, saturating after approximately 5-10 years at a factor of 2.5. A partial system re-design and the establishment of new systems further build on non-technical change. These offer higher factors - a factor 5 in medium-term and a factor 10 in long-term, respectively.

There is a small but growing number of empirical studies on the relationship between green technical change and its determinants. For reviews see Jaffe et al. (2003), Vries and Withagen (2005), Popp et al. (2009), and Horbach (2008). The difficulty for an empirical analysis is the identification of appropriate variables. For example, it is not possible to directly observe the shadow price[7] of environmental impacts or to simply extract environmental innovation data from existing innovation statistics. Moreover, specific indicators have just recently been introduced or are still under development. However, typical proxies of eco-innovations are patent numbers as well as R&D related expenditure and structures.

Empirical studies show that relative prices of inputs are a main driver of green technical change. Newell et al. (1999) confirm that energy prices induce energy efficiency of household appliances. The authors analyse US patents of room air conditioners between 1958-1993, central air conditioners between 1967-1988, and gas water heaters between 1962-1993. Apart from changes in relative prices, oil shocks in the 1970s had a strong influence on improvements in energy efficiency. Grupp (1999) use German patent indicators as well as oil import costs and find a positive impact of price signals on sustainable innovation in the long-run. Popp (2002) examines a strong positive impact of the energy price on energy efficiency innovation in US energy patent data from 1970-1994. Rennings

[7] The shadow price is the price resulting when all environmental impacts are considered. See also the next section on the concept of externalities.

and Rammer (2009) survey 29,486 German firms (response rate 20 %) and find cost savings to be a main incentive for energy and resource efficiency innovation. This is also the result of another survey of German panel data, Horbach (2008). Carrion-Flores and Innes (2010) confirm the cost-saving benefits of green R&D, analysing patent data in US manufacturing industries between 1986-2004 and toxic pollutant emissions.

One angle of technology and environmental policies is thus to influence technical change via input prices, e.g. by providing subsidies to reduce production costs or by imposing taxes or restrictions on certain inputs. Accordingly, the majority of studies confirm that (environmental) policy itself is a main driver of innovation. Grupp (1999) finds policy to be an important short-run driver. Brunnermeier and Cohen (2003) detect a small, but significant increase in environmental innovation with abatement costs for patents of US manufacturing industries between 1983-1992. Lanoie et al. (2007) surveying 4200 facilities from the 2003 OECD data base, with a response rate of 25 %, state that environmental policies induce cost-saving R&D, and that policy stringency is important. This is also found by Horbach (2008) who surveys data of German manufacturing and service firms from two panels.[8] An exception is Jaffe and Palmer (1997) who do not find a significant relationship between the stringency of environmental regulation (measured by compliance expenditure) and innovation activities of firms even though regulation induce R&D increases.[9] Instead, the effect of stringency on green R&D is only significant if an industry-specific filter is used. De Vries and Withagen (2005) study three different empirical models for SO_2 abatement policies and their impact on national environmental R&D using the EU Patent Office database for 1970-2000. The first model captures the effect of policy stringency on patents, considering the development of international agreements and domestic changes in abatement protocols simultaneously. The second model approximates the level of policy stringency by an 'index of environmental sensitivity performance'. Different pollutants are included but the international stringency level is assumed to be constant over the years. The third model studies the impact of national emission levels on green R&D, assuming that environmental strictness is not directly observable (treated as a latent variable). Only in the third model, the most realistic according to the authors, is the relationship between environmental policy stringency and innovative activity significantly positive. Recently, Johnstone et al. (2010) examined the influence of environmental policy in terms of stringency, predictability, and flexibility. Cross sectional data from the OECD EPO database[10] for the air, water, and waste sector confirm the hypothesis that policy stringency has an effect on invention and that policy predictability as well as policy flexibility have an effect on invention above and beyond policy stringency.

[8] The Mannheim Innovation Panel was established in 1993. In 2001, questionnaires also gathered environment related data (response rate: 20 %). The establishment panel of the Institute for Employment Research was founded in 1993. It contains data of 753 firms that belong to the environmental sector. Environmental innovation related questions are available for 2001 and 2004.

[9] A reason might be that policy compliance costs are not an appropriate variable (Jaffe and Palmer, 1997).

[10] State of the art in 2008. Collected data are from 1975-2007. Innovation was classified and only high-value patents were counted.

Source	Relationship between	Data set	Main finding
Newell et al. (1999)	energy efficiency of household appliances and energy prices	room air conditioners 1958-1993, central air conditioners 1967-1988, gas water heaters 1962-1993	inducement by energy prices, partially autonomous technical change, oil shocks are relevant
Jaffe and Palmer (1997)	stringency of environmental regulation and innovative activities of firms	US manufacturing industry patents and environmental compliance cost data 1973-1991	no significant relationship, small positive when controlling for industry-specific effects
Grupp (1999)	short- and long-run input price signals and sustainable innovation	DE patent indicators, oil import costs, sector-expenditures for environmental protection	long-run positive effect, short-run: governmental regulation and procurement are important drivers
Popp (2002)	energy price and energy-efficient innovation	US energy patent data 1970-1994	strong positive impact, importance of stock of knowledge
Brunnermeier and Cohen (2003)	abatement pressure and environmental innovation	US patents in manufacturing industries 1983-1992	small, but significant increase
Vries and Withagen (2005)	environmental stringency and country level innovation in EU	EU Patent Office database 1970-2000	only significant positive in model including emission levels
Mazzanti and Zoboli (2006)	firm characteristics, costs, policy pressure, and environmental R&D	Data of North Italian manufacturing firms 2002-2004	importance of networking, among other drivers

Table 2.1.: Empirical findings on determinants of eco-innovations, 1999-2006.

Source	Relationship between	Data set	Main finding
Rennings et al. (2006)	EMAS and environmental innovation	DE EMAS data	positive relationship, R&D department is a further trigger
Lanoie et al. (2007)	environmental policy and green R&D	survey of OECD data 2003 (4200 facilities)	policy induces cost-saving R&D, stringency is important
Horbach (2008)	environmental innovation and various drivers	Mannheim Innovation Panel (2001), Institute for Employment Research Panel (2001, 2004)	importance of knowledge capital, soft skills, cost savings, expected future demand, and policy incentives
Rennings and Rammer (2009)	energy and rescource efficient innovation and drivers	DE innovation survey (29.486 firms)	cost savings are main incentive
Carrion-Flores and Innes (2010)	toxic pollutant emissions and environmental innovation	patents and emissions in US manufacturing industries 1986-2004	significant negative, cost-saving benefits of green R&D, policy stringency increases incentives
Johnstone et al. (2010)	stringency, predictability, flexibility of environmental policy and innovation	OECD EPO database for air, water, and waste (1975-2005)	positive impact of stringency on patent activity, predictability and flexibility bring additional increases

Table 2.2.: Empirical findings on determinants of eco-innovation, 2006-2010.

Important drivers of green technological change are the availability of knowledge and R&D structures in a firm (Popp, 2002; Rennings et al., 2006; Mazzanti and Zoboli, 2006; Horbach, 2008), networking activities (Mazzanti and Zoboli, 2006), the introduction of EU Environmental Management and Auditing Schemes (EMAS) (Rennings et al., 2006), and the expected future demand (Horbach, 2008). The previous economic performance as well as the utilisation of capacities have no or a small influence on eco-innovation (Mazzanti and Zoboli, 2006; Horbach, 2008). Rennings and Rammer (2009) and Horbach (2008) also study the difference between firms that are in general innovative and firms that are specifically eco-innovative. According to Rennings and Rammer (2009), the later face stronger barriers. Horbach (2008) finds that the expectation of higher employment levels, demand, size of the firm, and highly qualified employees are relevant for both types of innovative firms. Regarding the policy influence, subsidies are an important trigger. Eco-innovation is strongly influenced by policy regulation, environmental management tools, and strategic and organisational changes. A synopsis of empirical studies is provided in Tabs. 2.1 and 2.2.

2.2. Rationale for policy interventions

2.2.1. Market failures and inefficiencies in the innovation system

The market potential of technologies to mitigate climate change is lower than their economic potential[11] (IPCC, 2007). The reason for this imbalance is the existence of externalities, i.e. the existence of benefits and costs that are not reflected through the price mechanism. They are imposed on or spill over to other parties than the economically active ones. An example of a negative externality is nutrient contamination of the Baltic Sea by agriculture and forestry causing coastal euthropication and thus imposing burdens on inhabitants and visitors. A positive externality would be e.g. the voluntary cleaning of a river by members of a local community. In this case, benefits spread beyond the group of activists. Externalities cause markets to fail and lead to inefficient innovation systems driving a wedge between private and social costs[12] and their theoretical optimum. In the case of green technological progress, there are negative environmental and - in sum - positive knowledge-related externalities.[13] Both interact with each other and influence the rate as well as the direction of green technological progress.

First, knowledge has the characteristics of a public good. Knowledge created by one

[11]The market mitigation potential is defined as 'the mitigation potential based on private costs and private discount rates (reflecting the perspective of private consumers and companies)'. The economic mitigation potential is defined as 'the mitigation potential that takes into account social costs and benefits and social discount rates, assuming that market efficiency is improved by policies and measures and barriers are removed', (IPCC, 2007, p. 56).

[12]Social costs are the sum of private and external costs.

[13]For reviews on environment-technology externalities see Grubb and Ulph (2002), Jaffe and Stavins (1995), and Popp et al. (2009). Gillingham et al. (2009) focus on externalities of an energy-efficient technological change. Malerba (2009) and Aghion et al. (2009) discuss technology externalities from an evolutionary perspective. Faber and Frentzen (2009) review the application of evolutionary theory in environmental-economics.

party can be used by others without reducing its amount (Nelson, 1959; Arrow, 1959). This has consequences for entrepreneurs undertaking R&D, as other firms might benefit without paying. Therefore, the amount invested in R&D will be too low. Externalities also occur in relation to the production of knowledge. For example, the market value of a new technology increases the better it is sold. Experiences in adopting the technology spill over to other potential users - in this case also for the benefit of the inventor.[14] However, a firm counts only its own expenses and profits when deciding about R&D investments. Therefore, the firm will not consider the full earning potential.[15] Potential competitors can also have an influence on the decision of an inventing firm. Severe competition might increase investment efforts in order to realise advantages from being the first inventor.

The notion of 'potential competitors' raises a second issue. Markets for technologies do not fulfill the criteria for perfect competition. The reason is that the number of firms undertaking R&D in the same field is limited. Often, R&D markets are even monopolistic. Furthermore, information is incomplete. This is foremost caused by the uncertain nature of the innovation process. For example, as the success and failure of R&D and its commercialisation potential is not known beforehand, the decision to invest is complex and likely suboptimal. In addition, the inventor has to pay a high risk premium if borrowing money from capital markets. Thus, financing constraints are another barrier to R&D.[16] Information is also incomplete because knowledge is part of a firm's capital and hence incentives are low to share information. On the other hand, technological progress could be accelerated through cooperation. This is an argument for 'open science approaches' (Aghion et al., 2009). In total, knowledge and R&D spillovers are positive leading to under-investments. Therefore, the rate of technological progress is suboptimally low.[17] Indeed, empirical studies find that the private rate of return on R&D is about two to four times smaller than the social rate of return (Gillingham et al., 2009).

The third issue is related to environmental externalities. These are ubiquitously negative as costs for polluting the environment, over-exploiting natural resources, or unsustainably producing, marketing, and consuming are almost not considered nor fully paid by the polluter. An extreme example is the oil spill in the Gulf of Mexico caused by the exploded offshore oil platform 'Deepwater Horizon' in April 2010. Two months later, estimates for clean-up and legal expenses already amounted to 33 billion US dollars. First doubts are spreading whether BP is able to pay these expenses.[18] Such over-uses of the environment could be avoided (or at least lessened) if environmental inputs, e.g. clean air

[14] See Jaffe and Stavins (1995); Popp (2010) for further discussions on externalities related to the adoption and diffusion of new technologies and Gillingham et al. (2009) for adoption barriers in energy markets.

[15] See Grubb and Ulph (2002) on this 'stand-alone effect'.

[16] In addition, there is asymmetric information between the firm undertaking R&D and the financial institution. This can also lead to problems of adverse selection, moral hazard, or principal-agent constellations.

[17] The impact of knowledge spillovers on the *direction* of technological progress is indirect, e.g. by limiting invention possibilities and creating dependencies on research paths taken.

[18] The Wall Street Journal Online, June, 10, 2010. http://europe.wsj.com/ .

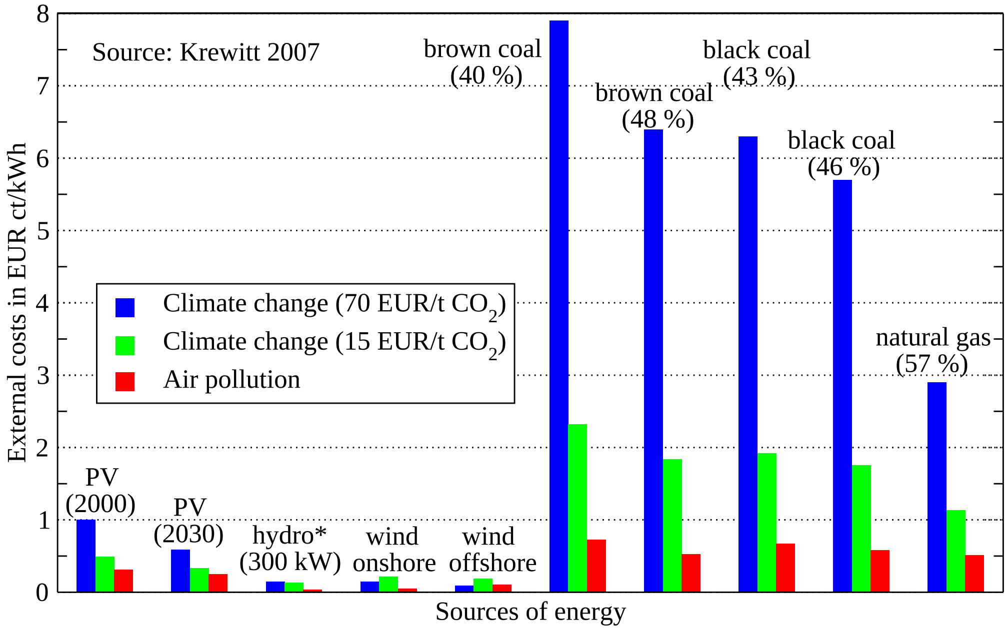


Figure 2.2.: External costs of different energy sources caused by climate change and air pollution.

and water, natural resources, etc., were not free and markets for these goods existed.[19] The prices for unsustainable products and processes would increase and in turn create markets for alternatives. Thus, environmental externalities primarily affect the direction of technological change.[20]

To illustrate the magnitude of environmental externalities, Fig. 2.2 and Tab. 2.3 show estimates of external costs for different fossil and renewable energy sources (Krewitt and Schlomann, 2007). For the fossil energy sources (brown coal, black coal, gas) assumed conversion efficiencies (steam power plants/ combined cycle power plants) are given in brackets.[21] The renewable energy sources are solar (photo voltaic, PV, and solarthermal power plants), on-shore wind (1.5 MW), offshore-wind (2.5 MW), and run-by-the-river hydro energy without water reservoirs (300 kW). External costs have been quantified[22]

[19]See Johnstone (2005) for a further discussion.

[20]National security issues, e.g. for the supply of energy, also influence the rate of green technological change (Gillingham et al., 2009).

[21]Steam power plants have assumed conversion efficiencies of 40% for brown coal and 43% for black coal. Combined cycle power plants have conversion efficiencies for brown coal of 48% and for black coal of 46%. Note that a conversion efficiency of 46% for black coal seems low in comparison to brown coal. Alternatively, other estimates predict at least 50% for a combined cycle power plant that uses black coal. See e.g. www.energie-fakten.de. The conversion efficiency of the gas power plant (combined cycle power plant) is 57%.

[22]Krewitt and Schlomann (2007) use the 'ExternE Method' that has been developed in a series of projects funded by the European Commission since 2001. See www.externe.info and Krewitt and Schlomann (2007). External costs are calculated by multiplying emissions per unit of electricity generation with

for damage categories 'climate change'[23], 'health risks', 'material damages', and 'crop losses'. The sum of external costs for electricity generation by renewable energies has been estimated to be below 1 EUR ct/kWh. The exception is photo voltaic energy. Under the current standard of technology, the production of solar cells is very energy intensive. In contrast to renewable energies, external costs of fossil fuels are found to range between 6-8 EUR ct/kWh. If we assume an average price of private costs for electricity generation of approximately 3.5 EUR ct/kWh, it is obvious that current private costs are far below social costs.[24] Fig. 2.2 shows that external costs of climate change dominate. This also holds if the lower estimate of 15 EUR/t CO_2 instead of the middle estimate of 70 EUR/t CO_2 is used for the calculation. The figure furthermore illustrates the imbalance between renewable and fossil energies. The latter have a substantial competitive advantage.

Concluding, externalities can lead to suboptimal economic activities of firms (or other agents), i.e. there is a wedge between related private and social costs. As more than one market failure is connected with the process of eco-innovation, the combination of different policy instruments comes to mind. An often used justification for policy interventions is that the double-externality problem can yield a double dividend[25], i.e. bring an ecological (social) and an economic (private) benefit. The latter can be realised through international competitive advantages for environmental technology leaders, compensating for costs from complying with environmental regulation. The environmental externality problem can be solved theoretically by adjusting prices for environmental consumption via Pigouvian taxes or subsidies (Pigou, 1920), introducing environmental/technology standards (Baumol and Oates, 1988), creating markets for environmental goods, introducing liability law, or starting information programmes (Coase, 1960). These basic principles translate into different environmental policy measures. Knowledge related externalities can be internalised by measures of technology policy, e.g. the promotion of R&D via research loans, subsidies, grants, and patent policies, the provision of information, and the support of research infrastructures. The following two sub-sections provide an overview of typical instruments of environmental and technology policy to encourage green technological progress as well as a discussion of their efficiency.

the specific damage costs. Impacts on the eco-system, geo-political effects, risks of proliferation, as well as risk of major catastrophes are described qualitatively.

[23]Estimates of social carbon costs strongly depend on the chosen discount rate and the factor 'equity weighting' that accounts for worldwide welfare differences. Krewitt and Schlomann (2007) compare different studies and follow Downing et al. (2005) with a middle cost estimate of 70 EUR per ton CO_2 equivalent (individual discount rate of 1%, equity weighting included). The low estimate is 15 EUR/t CO_2, the high 280 EUR/t CO_2.

[24]This is a rough estimate. The average end-user energy price for middle size households in Germany was 0.1401 EUR/kWh in 2009 (http://epp.eurostat.ec.europa.eu) whereof 25% come from electricity generation (http://strompreisentwicklung.org).

[25]See the discussion around the Porter hypothesis (Porter and v. d. Linde, 1995).

External costs in EUR ct/kWh	photo voltaic (2000)	photo voltaic (2003)	hydro (300 kW)	onshore wind (1.5 MW)	offshore wind (2.5 MW)	geothermal
climate change	0.69	0.38	0.09	0.07	0.06	0.26
health	0.34	0.20	0.06	0.07	0.03	0.12
material damages	0.009	0.006	0.001	0.001	0.001	0.003
crop losses	0.005	0.003	0.001	0.002	0.0004	0.002
Sum	∼1.0	∼ 0.59	∼0.15	∼0.15	∼0.09	∼0.39

External costs in EUR ct/kWh	solarthermal	brown coal (40%)	brown coal (48%)	black coal (43%)	black coal (46%)	gas (58%)
climate change	0.09	7.4	6.4	5.9	5.5	2.7
health	0.085	0.50	0.28	0.37	0.26	0.17
material damages	0.002	0.015	0.008	0.013	0.01	0.005
crop losses	0.001	0.010	0.004	0.009	0.005	0.004
Sum	∼0.18	>7.9	>6.4	>6.3	>5.7	>2.9

Table 2.3.: Quantifiable external costs of different energy sources. Source: Krewitt and Schlomann (2007).

2.2.2. Instruments of technology policy and environmental policy

The objectives of appropriate policy measures are to spur *and* direct technological progress towards its social optimum[26]. Therefore, environmental policy aims partially overlap with and partially contradict those of general technology policy.[27] For example, the EU provides large funds for the development of general-purpose technologies, e.g. internet technologies, space technologies, transport technologies, etc. These are not environmental technologies as they are likely to add further burdens on the environment. On the other hand, some of these technologies have the potential to contribute to a direct or indirect solution of environmental problems, e.g. by increasing the probability for a scientific breakthrough in the exploration of an environmental technology.

Environmental policy instruments, particularly those targeting firms, are commonly divided between market-based, regulatory (or command-and-control), and non-mandatory instruments. Pigouvian taxes, subsidies, and user-fees, as well as the creation of markets for pollution or emission rights belong to the first category. These instruments try to influence a firm's behaviour through market signals by increasing relative prices for environmental consumption. This promotes a general green technological progress since firms are free in their adaptive response. The category of regulatory instruments comprises environmental standards, technology and performance-based standards[28], bans, and input and output quotas, as well as environmental legislation, obligatory eco-labeling and management schemes. These instruments target specific eco-innovations (technology forcing). A firm has no (legal) option but to comply with the obligations. Examples for non-mandatory instruments are voluntary agreements and information programmes, e.g. to raise environmental awareness or to inform about less polluting alternatives. While not addressing firms, an important additional measure is green public procurement. It can foster the development and diffusion of environmental technologies.

Technology policy can be categorised depending on which innovation phase is primarily targeted or what side of the market - supply or demand - is mainly supported. Invention, innovation, as well as diffusion can be directly supported, e.g by providing loans, subsidies, tax advantages, or other incentives. These measures aim to increase R&D spending and technology investments. For reducing the impact of incomplete information, policies furthermore support R&D infrastructures and integrated research networks or carry out information programmes. Policies backing the supply-side are called technology-pull programmes. Those programmes supporting the demand-side are known as technology-push

[26] The social optimum in the static set-up can be achieved when the marginal social costs of environmental consumption equal the marginal social benefits from consuming the next unit of environment. These costs depend on the environmental-damage function which in turn is changing with technological progress. Therefore, in the dynamic set-up, the optimal level of innovation has to be also chosen by the social planner.

[27] See also Grubb and Ulph (2002) for a discussion of the objectives of environmental and energy policy. An example area of conflict would be energy security issues.

[28] This includes dynamic standards that provide incentives for a continuous improvement of eco-efficiency. An example is the Japanese Top-Runner Programme introduced in 1999. Regularly, new efficiency standards for the energy end-use of household appliances are set. The new standard is chosen *above* the current highest available standard and it has to be reached within a fixed period depending on the rate of technological progress.

Knowledge externalities: a) suboptimal R&D spending, b) incomplete information			
	Invention	*Innovation*	*Diffusion*
a)	R&D funding (loans, grants, subsidies, tax advantages etc.)	subsidies for market introduction, public green procurement, patenting	tax incentives and other adoption support, public green procurement
b)	integrated R&D funding, provision of infrastructure	information programmes, support of infrastructure and networks	infrastructure for technology transfer, information programmes

Environmental externalities I) market-based, II) regulatory, III) non-mandatory instruments			
	Invention	*Innovation*	*Diffusion*
I)	*for all phases:* environmental taxes, liability law, creation of markets for environmental goods (e.g. trading of emission rights)		
II)	*for all phases:* environmental standards, technology and performance based standards, bans, quotas, environmental legislation, obligatory management schemes		
III)	-	-	eco-labeling, public green procurement, information programmes, voluntary agreements

Table 2.4.: Innovation-oriented environmental policies (based on Rennings et al. (2008, p.35)).

programmes. Tab. 2.4 provides an overview of innovation oriented environmental policies. For a recent survey of theoretical and empirical issues of induced innovation and the 'tandem of environmental and technology policy' see e.g. Popp et al. (2009). Lehmann (2010) reviews the literature on policy-mix to prevent pollution. Rennings et al. (2008) discuss and evaluate eco-innovation instruments that are applied in Germany.[29]

2.2.3. Efficiency of policy measures

Neither the consumption of the environment nor its protection nor restoration come without costs. Moreover, environmental externalities are not the only ones that cause social costs (or concerns for the society). Therefore, internalisation measures should be enforceable and efficient. This depends on several factors such as the dynamic cost-efficiency of an instrument, its opportunity costs, the ability of policies to increase the rate and steer the direction of green technological progress, the best policy choice under uncertainty and in a complex world[30], an instrument's political feasibility, and its reliability. These factors influence the optimal choice of an instrument, its stringency level, and its timing.

There is a broad theoretical literature on dynamic incentives for environmental R&D investments. A basic distinction is made between model types, endogenous-growth models, and microeconomic decision-theoretic models.[31] Endogenous Growth Theory studies the implications of R&D and the role of policy at an aggregate level by introducing innovation possibility frontiers or modelling knowledge as a capital stock. Its main interests are imperfections in innovation markets (knowledge spillovers, crowding out effects) and substitution effects between the generation of output and the generation of new knowledge. Many theoretical and numerical models have shown that, first, cost effects from policy measures (resulting in lower per-capita incomes) are larger than the compensating effects of induced innovation, and second, general R&D can be crowded out by environmental R&D. However, the opposite can also be the case.[32] Decision-theoretic models are basically partial equilibrium models. The decision of a policy-maker or firm/sector is analysed in (finite) subsequent stages as an optimal control problem. Here, the topics of interest are innovation incentives and welfare implications under perfect or imperfect competition, with or without strategic options. The distinction between R&D investment and adoption investment is not always clear. Requate (2005, p. 179) defines that a model is primarily an innovation model if 'there is a stochastic element, i.e. the size of innovation, its date, or the R&D success is uncertain, or secondly, a patent is granted on the innovation, or thirdly, spillovers occur, or finally, imitation is possible.'

The ranking of policy instruments is ambiguous. But instruments that influence relative prices and allow flexibility are often preferable over regulative instruments, because

[29] See also Section 2.1. for empirical findings on the determinants of eco-innovation that include policy as an important driver.

[30] Note that damage functions, social optima, and policy impacts can only be estimated.

[31] The following summary uses the reviews of Requate (2005), Jaffe and Stavins (1995), Goulder and Parry (2008), and Popp et al. (2009). Note that we are not including findings on technology diffusion and adoption.

[32] For example, carbon-energy saving R&D replaces carbon-producing R&D instead of crowding out neutral R&D when the three are modelled separately (Popp et al., 2009).

market-based instruments enable adoption at least cost and provide incentives to continue R&D activities with a free choice of technology to achieve further cost reductions. This is not the case for (static) regulatory instruments as there is no additional reward in exceeding performance standards or choosing a technology, in the case that incentives are connected with a certain technology. However, regulatory instruments are at an advantage in the effective cutting back of the level of environmental pollution or emission. Furthermore, by defining dynamic standards, the problem of a 'technology freeze' (Popp et al., 2009) can be avoided, e.g. by setting technology standards according to the best-available control technology at a time. A disadvantage is that regulatory instruments become more vulnerable to issues of policy commitment and time consistency.

Models that study these factors take account of the possibility of firms and regulators to anticipate and/or react to each others decisions. For example, regulators may choose to adjust their policies after observing innovation effects (e.g. after listening to winners and loosers of a new regulation) or simply because policy priorities change. Policy commitment and timing in these models is then a matter of the social costs of pollution. The level of environmental stringency has two antipodal effects. On the one hand, as costs increase with stringency, incentives for R&D increase. On the other hand, R&D incentives decrease as less output can be produced. Competition models show that technology leaders are in favour of higher environmental stringencies. However, the total effect (and thus the policy ranking) depends on the magnitude of knowledge spillovers and their appropriability, marginal abatement cost curves, as well as characteristics in environmental technology markets (market power, number of firms, etc.). Many empirical studies support the important role of environmental policy and stringency to promote green technological progress (see Section 2.1). Both market-based instruments as well as regulatory instruments spur innovation and induce cost-reduction.

In the majority of environmental-economics studies, uncertainties are not taken into account when analysing the efficiency of policy measures. This lack in the literature and its impacts on decisions to invest in green R&D will be tackled in the following section.

2.3. R&D decisions in a complex world

2.3.1. The role of irreversibilities and uncertainties

Irreversibility causes destabilisation processes that are connected with forgone options. Examples for such forgone options are the lost option to maintain an ecological system, e.g. the diversity of populations (Holling, 1973),[33] the lost option of using a natural environment, e.g. caused by technically irreversible construction projects in a redwood forest (Arrow and Fisher, 1974),[34] the decreased variety of investment choices or managerial flexibilities (Henry, 1974; Dixit and Pindyck, 1994),[35] or the loss of the development of superior technologies due to historical lock-in phenomena (Arthur, 1989)[36]. Generalising these examples, we will use the following definition

> *Irreversibility is a measure of the difficulty of returning to an initial state within an economically meaningful time frame following a perturbation. (Perrings and Brock, 2009, p. 224)*

The reference to an 'economically meaningful time frame' has two implications. First, the definition includes more than strictly non-reversible systems. A reversible system can be interpreted as an irreversible one if the speed of adjustment to a perturbation is large in relation to the time horizon of the decision-maker. Second, it is assumed that the backward-transformation can be expressed in cost categories. As a consequence, irreversible decisions are associated with sufficiently large reversion costs. To give an example, the irreversibility of capital investments is generated by the non-malleability of capital (Perrings and Brock, 2009) resulting in sunk costs. According to Dixit and Pindyck (1994), sunk investment costs can occur due to firm- or industry-specific investments, an under-evaluation of goods in second-hand markets, and governmental or institutional regulation.[37]

[33] Holling (1973, p. 17) establishes a link between irreversibility and the resilience of a system. Resilience 'determines the persistence of relationships within a system and is a measure of the ability of these systems to absorb changes of state variables, driving variables, parameters, and still persist. In this definition resilience is the property of the system and persistence of probability of extinction is the result'. Therefore, a system is irreversible if it has lost its resilience.

[34] Arrow and Fisher (1974, 314) associate irreversibility with reversion costs. The time to transform a natural environment backward 'is so great that, given some positive rate of time preference, it might as well be irreversible.'

[35] Henry (1974) states that 'a decision is considered irreversible if it significantly reduces for a long time the variety of choices that would be possible in the future'. In Dixit and Pindyck (1994), irreversibility is expressed as sunk investment costs.

[36] Arthur (1989, p. 117) relates irreversibility to the choice of one out of multiple equilibria resulting in non-ergodicities and inflexibilities such that 'once an outcome (a dominant technology) begins to emerge it becomes progressively more locked in'.

[37] The inclusion of irreversibility and uncertainty when deciding about capital investments is subject to the theory of real options. Myers (1977, p. 22) introduces this term as an analogy to financial options, i.e. real options 'are opportunities to purchase real assets on possibly favorable terms' and 'the value of real options reflects the possibility of rents or quasi-rents'. Thus, capital investments can be treated as an American call option, i.e. the holder has a right to invest money (call) and the option can be exercised at any time (American). The return on investment is a package of some value that can be sold. The investment itself, however, is irreversible as costs are sunk. Note that

The source of a perturbation can differ. Its impact on the evolution of the system, i.e. the direction and magnitude of effects, strongly depends on the interplay between uncertainties, non-linearities, and the time horizon. Obviously, uncertainty is larger the greater the time horizon is - to guess what happens tomorrow is easier than to guess what happens in the next century. Moreover, with time passing, hysteresis effects and catastrophic events can occur, whose aftermaths are highly non-linear and irreversible, further complicating a prediction of the system's evolution.

Before we present the main literature findings on the uncertainty-irreversibility relationship, we will specify what is meant with 'uncertainty'. We will adopt the following definition by Milliken (1987)

> *Uncertainty is 'an individual's perceived inability to predict something accurately'. (Milliken, 1987, p. 136).*

Thereby, the source of uncertainty is external to the individual or its organisation. This is captured by the term 'environmental uncertainty' and implies that uncertainty is not a matter of objectiveness. Uncertainty originates from the inability of agents to assign probabilities to future events or to gather and evaluate information of causalities between system variables and their impacts. Milliken (1987) distinguishes between three types of environmental uncertainty. These are state uncertainty, effect uncertainty, and response uncertainty. The first derives from not knowing and understanding how system components (state variables) change and are interrelated. For example, a firm is unable to predict changes in environmental policy or the behaviour of competitors. Effect uncertainty concerns the inability to foresee impacts of changes in the environment on the agent's organisation. For example, the Federal State of Mecklenburg-Vorpommern is uncertain about how climate change will impact the region's water levels. The third category, response uncertainty, relates to the inability to identify all responsive options or evaluate them. Fig. 2.3 illustrates this hierarchy of uncertainties from the perspective of a single firm.

The self-amplifying interplay of irreversibility and uncertainty (Pindyck, 2007) can lead to suboptimal decisions that are able to alter the micro- as well as the macro-system. Arrow and Fisher (1974) find suboptimality in the social point of view. Irreversibility adds an extra value to the reversible alternative. This value is called the option value and creates an irreversibility bias in comparison to classical valuation methods. Kassar and Lasserre (2004), among others, consider the possibility that species become extinct. Similar to Arrow and Fisher (1974), uncertainty increases the value of biodiversity. Thus, in these models, irreversibility reduces investment benefits and raises the opportunity costs for developing a natural environment. Hence, an optimal policy under uncertainty is to hesitate developing the natural habitat, keeping flexibility and not restricting future options. A similar value of waiting is created in models with market uncertainty (Dixit

the option is competitive as it is open to others. Real options models belong to the class of partial equilibrium models. Their main interest is to study the impact of irreversibility and uncertainty on the critical investment threshold. See Dixit and Pindyck (1994) for a classical monograph on real options. See Adner and Levinthal (2004) for the limitations of the approach. Section 3.2 reviews the literature on real options for R&D investments.

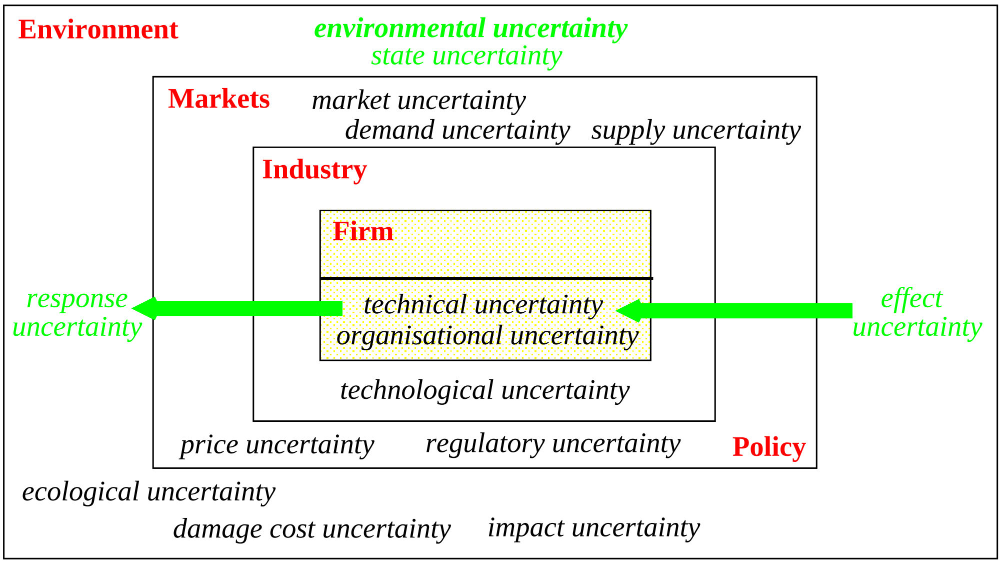


Figure 2.3.: Hierarchy of uncertainties from the perspective of a single firm.

and Pindyck, 1994, among others).[38] It arises from the possibility of updating information as time passes (Bayesian learning). Pindyck (2002) analyses the optimal timing of environmental policies, i.e. an earlier vs. a later one-time adoption of an emission reducing policy. The model yields a value in postponing a policy decision, lowering the benefits of an intervention.

However, the sign of the generated option value is ambiguous. Uncertainty can accelerate or hamper capital investments (or an activity in general). The direction depends on the type of uncertainty and its structure. If investing (or some activity) can reveal information, expanding the investment (or activity) is more valuable. If otherwise, learning is passive, the incentive to wait increases with irreversibility and uncertainty (see e.g. Pindyck (1993); Leahy (1996); Ulph and Ulph (1997); Kort (1998)). The reason for the postponing effect is that uncertainty imposes risks for reversing the activity without creating prospects for its continuation. However, there are also factors that are able to alter the negative investment-uncertainty relationship in models with a passive resolution of uncertainty. Caballero (1991) studies the role of decreasing returns to scale or imperfect competition. He finds that under a negligible degree of imperfect competition the relationship between investment and uncertainty is positive. The same applies if competition is very high. In the latter case, the price of capital and its expected marginal profitability become the dominating factors instead of the asymmetric adjustment costs. Bar-Illan and Strange (1998) analyse the option to abandon a project (with costly exit

[38]Note that the option value in Arrow and Fisher (1974) and Henry (1974) is connected to the value originating from the real options theory of Dixit and Pindyck (1994). Fisher (2000) argues that both are equivalent. But Mensink and Requate (2005) suggest to separate the real option value into two parts - a value of obtaining new information equivalent to the theory by Dixit and Pindyck and a second part deriving from lost benefits when postponing the decision.

and entry) and the influence of an interest rate. In both cases, the marginal revenue from the capital, the net present value, is a convex function of the variables. This leads to a positive sign of the investment-uncertainty relationship. Sarkar (2000) finds that the probability to invest increases with uncertainty for low-risk and slow-growth projects.[39]

Table 2.5 provides an overview of the types of uncertainties that have been studied. We use the hierarchy of uncertainties by Milliken (1987) to structure this line of research. The table shall serve as an entry point into the literature sorting early publications as well as the emerging literature in environmental-economics that considers uncertainties and/or irreversiblities and their influence on a decision-maker. Examples of two-period models as well as time-continuous models are included. Some publications solely take into account uncertainty. Furthermore, in a few cases, uncertainty is not a stochastic variable but switches between deterministically chosen values. The discussion of findings is postponed to the next section.

One might argue that uncertain variables could be replaced by their expectation values and that this approximation is good enough for good estimates. However, Henry (1974) as well as Arrow and Fisher (1974) have shown that suboptimal investment paths are chosen under such a simplification. This is a consequence of irreversibility, non-linear relations, and functionalities that are typical if the time horizon is long and uncertainties are large.[40] Apart from costs and benefits, discount rates are also a matter of the uncertainty-irreversibility discussion. Replacing these with their expected values leads to a smaller discount factor and the error accumulates rapidly with time. Therefore, the 'effective discount rate' (Pindyck, 2007) needs to be much lower than the expected. Using IPCC estimates for climate sensitivity and policy costs, Golub et al. (2009) determine the distribution of avoided climate change damages vs. sunk mitigation costs in a numerical simulation. The latter turn out to be larger but the potential damages show a greater variance. More importantly, the potential damages have a fat tail in the distribution. This fat tail is caused by the high risk for catastrophic events. Golub et al. (2009) conclude that models based on the expectation value method averaging these kind of effects out are not suitable. Hence, alternative methods are called for (e.g. probabilistic approaches, real options theory).

There are a few empirical findings on the effects of irreversibility and uncertainty. We will shortly summarise the results of these publications focussing on the effects of investment decisions. Bulan (2005) confirms that industry and firm-specific uncertainty can create an option to delay investments but competition can accelerate them. Using data from the German manufacturing sector 1995-2001, Czarnitzki and Toole (2008) also find

[39] This is a controversial finding, see e.g. Lund (2005). Similar to Sarkar (2000), Lensink (2002) studies an empirical model of aggregate investments for a set of developed countries. He finds that low levels of uncertainty are likely to accelerate investments whereas high levels hamper investments.

[40] Note that it is typically assumed that cost and benefit functions are not linear but quadratic. Pindyck (2007) gives a simple example of the difference for the calculation of abatement cost when expected values are used to replace uncertain variables. Abatement costs C are given by $C(A, \epsilon) \approx [(1+\epsilon)A]^2$. A is the abatement level in percentage. ϵ is a random variable that takes -1 or +1, each with a probability of 0.5. Thus, abatement costs equal A^2 when using the expected value of ϵ, $E[\epsilon] = 0$. On the other hand, $E[C(A, \epsilon)] = 0.5\,C(A, -1) + 0.5\,C(A, 1) = 2A^2$ when directly using the definition of the expectation value.

Ecological uncertainty	
impact uncertainty:	Chao and Wilson (1993); Kolstad (1996); Pizer (1999); Pindyck (2002); Fisher and Narain (2003); Kassar and Lasserre (2004); Wirl (2006); Baker et al. (2006); Lin et al. (2007); Baker and Adu-Bonnah (2008); Golub and Markandya (2009); Goeschl and Perino (2009); Ansar and Sparks (2009)
damage cost uncertainty:	Laffont and Tirole (1996); Ulph and Ulph (1997); Pindyck (2002); Newell and Pizer (2003); Lin et al. (2007); Baker and Adu-Bonnah (2008); Blanford (2009); Bosetti et al. (2009)
Market uncertainty	
benefit uncertainty:	Weitzman (1974); Arrow and Fisher (1974); Stavins (1996); Hassett and Metcalf (1999); Ansar and Sparks (2009)
cost uncertainty:	Weitzman (1974); Stavins (1996); Menanteau et al. (2003); Zhao (2003); Laurikka and Koljonen (2006); Fuss (2010)
demand uncertainty:	Caballero (1991); Chao and Wilson (1993)
Regulatory uncertainty	
regulatory uncertainty:	Larson and Frisvold (1996); Farzin and Kort (2000); Isik (2004); Baker and Shittu (2006), this thesis
Industry-wide uncertainty	
technological uncertainty:	Pizer (1999); van Soest and Bulte (2001); van Soest (2005); Ohyama and Tsujimura (2008); Goeschl and Perino (2009); Fuss (2010)
Firm-specific uncertainty	
technical uncertainty:	Grossman and Shapiro (1986); Pindyck (1993); this thesis

Table 2.5.: Literature studying different types of uncertainties and their influence on a decision-making institution.

that strategic rivalry increases the option to postpone investments. Another result is that large firms are less responsive to market uncertainty. Using US firm panel data, Baum et al. (2008) confirm that firm-specific uncertainty and market uncertainty are significant. In particular, firm-specific uncertainty is more important for investment decisions than market uncertainty. Studying UK manufacturing companies for the years 1972-1991, Bloom et al. (2007) find that uncertainty generates a significant 'cautionary effect'. They conclude that in times of high uncertainties, firms might respond to policy incentives weakly. Hoffmann et al. (2008) develop a taxonomy for regulatory uncertainty that they apply to the European Emission Trading Scheme launched in 2005. They estimate that regulatory uncertainty has a significant impact in all four categories. Uncertainties concern the basic direction of regulation, measures and rules, the implementation process, as well as interdependencies. Johnstone and Hascic (2009) also study the impact of regulatory uncertainty using the World Wide Statistical Database PATSTAT from 2008. The more unpredictable environmental and technology policies are, the smaller the induced-innovation effect, and the longer investments are postponed. Moreover, unstable policies can create market uncertainty. Finally, Lensink (2002) finds evidence for a non-linear investment-uncertainty relationship providing an explanation for the ambiguous findings on the sign of the relationship. In a quantitative case study of the Finnish electricity sector, Laurikka and Koljonen (2006) analyse the influence of the European Emission Trading scheme (EU ETS) on investments under uncertainty of the baseline fuel price and the price of emission allowances. Investors have the option to switch investments between coal-fired plants and gas-fired plants or to postpone investments. The EU ETS influences the decision through output prices, the value of surrendered allowances, operating hours, and the value of free allowances allocated for installations. Uncertainty about the impact of the EU ETS on these parameters decreases investments in gas plants. In particular, high uncertainty regarding the allocation of free allowances is decisive for switching to gas. Interestingly, renewable energy and nuclear power plant investments are not affected by this type of uncertainty.

Of course, not all decisions under irreversibility and uncertainty decisively transform the system or alter optimal policies. Pindyck puts up the following condition for environmental policies: 'irreversibility will affect current decisions if it would constrain future behaviour under plausible outcomes' (Pindyck, 2007, p. 56). Even though irreversibilities and uncertainties alone do not cause market failures, one might argue that policies could aim to reduce uncertainties and hence lessen their impact on environmental and knowledge externalities. Indeed, instruments like fluctuation margins, safety valves, or guaranteed prices aim for this. See e.g. Goulder and Parry (2008) for a discussion. However, such kind of policies lead to a trade-off between adjusting policies with the arrival of new information and not causing policy uncertainty themselves. Furthermore, policies also contain large irreversibilities making policy failures costly. Still, Aghion et al. (2009) argues in favour of the common 'environmental cautionary principle' stating that inactivity might also not be an option. Nordhaus and Popp (1997) derive the value of resolving uncertainty within a global warming model. It can be used to get an understanding of the relevance of uncertainties in this context. Nordhaus and Popp (1997) consider uncertainty about the slowdown in the growth of population and production, the accumulation rate of green house gases, climate feedbacks, time preferences, the output rate of green house gases, and the costs of mitigation. They find that these parameters cause substantial uncertainty about climate change costs and benefits as well as optimal policy responses. Finally, Nordhaus and Popp (1997) estimate the value of perfect foresight. Knowing all about 2045 already today (1995) is worth between 45 and 108 Billion US dollars. Most valuable is information about climate change damages followed by resolved uncertainty about the emission reduction costs, the relationship between temperature and carbon dioxide, the growth in population, the de-carbonisation rate, the atmospheric retention rate of carbon-dioxide, and the future growth in productivity. Nordhaus and Popp (1997) estimate that resolved uncertainty involving behavorial and social sciences accounts for 85 % of the total value, whereas uncertainties involving natural sciences contribute 15 %.

Therefore, it is useful to better understand the impact of environmental policies on investment decisions towards green technologies. Uncertainties most relevant in this context are apparently those connected with the ecological system, e.g. the impact of climate change and cost of mitigation measures, as well as uncertainties occurring within the stages of innovation. Indeed, the optimal policy strongly depends on and varies with the available knowledge about the technological progress. Concerning ecological uncertainty, parameters and shapes of damage cost functions are largely uncertain (Pindyck, 2007). Also not known is the probability distribution for catastrophic events as well as future social discount rates. Regarding the innovation process, some uncertainties are likely to be more relevant in one stage than in another. Earlier stages in the innovation process are more influenced by supply-side factors such as input prices, output prices, policy parameters, technical uncertainty, and market power. But for the diffusion of environmental technologies demand-side uncertainties are more decisive.[41] Here, the most relevant irreversibilities are sunk cost of policy intervention, sunk cost of complying with policy measures, and sunk cost of investment decisions.

2.3.2. Green technological progress, uncertainty, and environmental policy

In a seminal paper studying the impacts of uncertainty on the choice of quantity and quality instruments, Weitzman (1974, p. 482) states an important result of a two-period model:

> *In the presence of uncertainty, price and quantity instruments transmit central control in quite different ways. It is important to note that by choosing a specific mode for implementing an intended policy, the planners are at least temporarily locking themselves into certain consequences. The value of η and θ are at first unknown and only gradually, if at all, become recognized through their effects. After the quantity $\hat{q}$ is prescribed, producers will continue to generate that assigned level of output for some time even though in all likelihood*
>
> $$B_1(\hat{q}, \eta) \neq C_1(\hat{q}, \theta) \ .$$

[41] See also Section 2.1 for the drivers of green technological progress.

> *In the price mode on the other hand, $\tilde{q}(\theta)$ will be produced where except with negligible probability*
>
> $$B_1(\tilde{q}(\theta), \eta) \neq C_1(\tilde{q}(\theta), \theta) \ .$$
>
> *Thus neither instrument yields an optimum ex post. The relevant question is which one comes closer under what circumstances.*

Here, η is the random variable in the function describing expected benefits B_1. θ is the random variable in the expected cost function C_1.

As marginal benefits do not equalise marginal costs, both policies are not first best policies when uncertainty and irreversibility are present. The ranking of the instruments depends on the slope and structure of benefit and cost functions.

Weitzman (1974) assumes a quadratic form for both. After the policies have been fixed, agents choose their optimal output depending on the stochastic price. Outputs are denoted by $\tilde{q}$ in case of the price and $\hat{q}$ in case of the quantity regime. In order to compare the two regimes, Weitzman (1974) studies the expected comparative advantage of the policies

$$\Delta = E\left[B(\tilde{q}(\theta), \eta) - C(\tilde{q}(\theta), \theta) - (B(\hat{q}, \eta) - C(\hat{q}, \theta))\right] \ , \tag{2.1}$$

with E being the expectation value operator. The transformation of Δ and the execution of the expectation value yields the interesting finding that the ranking of the policy regimes under uncertainty is ambiguous. Why is this so? First, let us only consider uncertainty of benefits. In this case, outputs are the same under both policies as corresponding marginal costs are not influenced by this type of uncertainty. But adding cost uncertainty introduces asymmetry to the decision problem. In the quantity regime, marginal costs become uncertain. In the price regime, the output level $\tilde{q}$ becomes uncertain.[42] It turns out that the slope of marginal benefit and cost functions is the decisive parameter for the policy ranking as

$$\Delta \ = \ \frac{\sigma^2}{2C''^2}(B'' + C'') = \begin{cases} > 0 & \text{if } |B''| < |C''| \ , \\ < 0 & \text{if } |B''| > |C''| \ , \end{cases} \tag{2.2}$$

where σ^2 is the variance in relation to θ. Note that $B'' < 0$ and $C'' > 0$. Therefore, if expected marginal benefits are relatively flat in comparison to expected marginal costs, the price instrument results in smaller deadweight losses (see the left-hand side in Fig. 2.4). The influence of θ on actual benefits is relatively small even for a broad margin of cost fluctuations. Thus, the optimal output-bias in the price regime is relatively small when comparing optimal levels before and after the resolution of uncertainty. The opposite is the case if expected marginal benefits are relatively steep (see the right-hand side in Fig. 2.4). The deadweight loss in the quantity regime decreases, whereas it

[42] Weitzman (1974) makes a quadratic approximation. He henceforth allows only small fluctuations of $\tilde{q}(\theta)$ around $\hat{q}$. This leads to benefit functions and cost functions that are dependent on $q - \hat{q}$, only. Their expected marginal values are then denoted by $C' = E[C_1(\hat{q}, \theta)]$ and $B' = E[B_1(\tilde{q}, \eta)]$. The second derivative describes the slope of these functions.

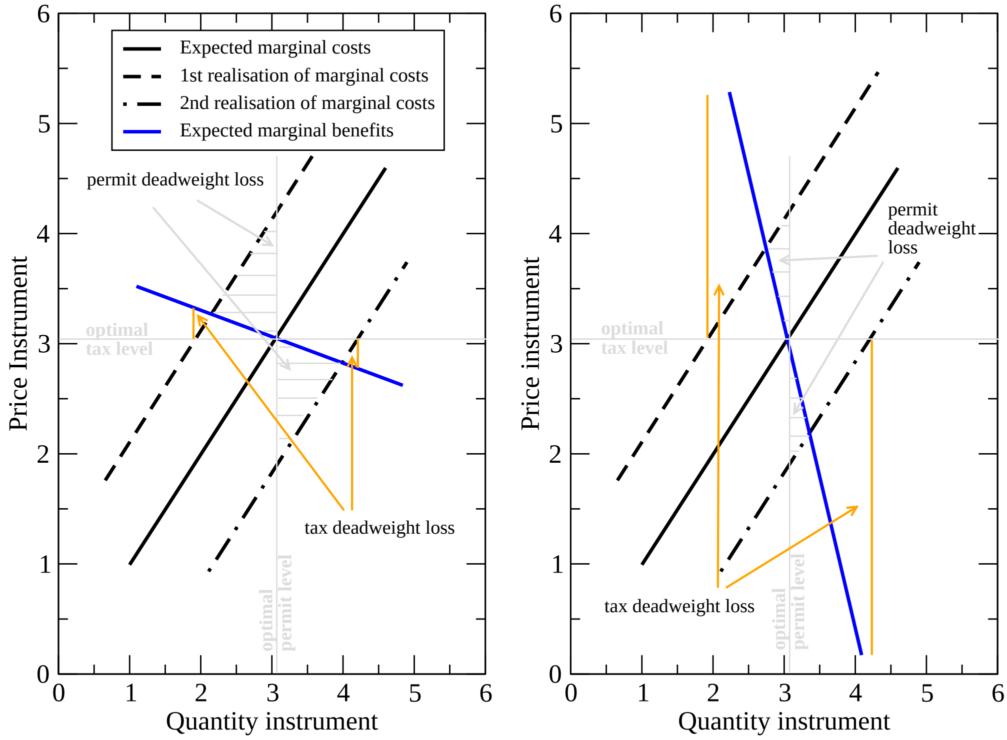


Figure 2.4.: Deadweight loss of price and quantity instruments under uncertainty. Source: Pizer (1997), p.5.

increases in the price regime. This time, benefits are more sensitive to the stochastic parameters. But the resulting broad margin has only a small impact on the optimal output. Thus, the uncertainty result under the quantity regime is relatively close to the optimal policy when assuming certainty.

Subsequent to the publication of Weitzman (1974), the impact of uncertainty and irreversibility on the efficiency of policy instruments has been subject to several studies. In what follows, we will review recent theoretical literature with respect to 1) the choice of the policy instrument, 2) the intensity of environmental policy, 3) the timing of environmental policy, 4) the impact of policy uncertainty, and 5) uncertainty of the green technological progress. Tables in Appendix A.1 summarise the review.

1. Choice of environmental policy under uncertainty

Weitzman's comparison of prices vs. quantities has been extended by Stavins (1996), who allows for correlations between cost and benefit uncertainties, and Newell and Pizer (2003), who develop a time-continuous model. Stavins (1996) finds that covariance can change the ordering. In case of a positive correlation, quantity instruments are favoured. In case of a negative correlation, price instruments are the better choice. The size of this effect is proportional to the correlation parameter and the magnitude of costs and benefits. In addition to theoretical analysis, Stavins (1996) performs a numerical application with realistic parameters, yielding the preference of quantity instruments. Newell and Pizer (2003) confirm the decisive impact of slopes of marginal benefit and cost functions. They study the evolution of the stock of a regulated good under time-correlated costs. Quantity instruments perform better for lower stock decay rates, lower discount rates, higher rates of benefit growth, and higher correlation in costs across time. Pizer (1999) combines economic, climate, and trend models[43] with economic and climate change uncertainty[44]. He finds that taxes are preferable over output controls since marginal damages are relatively flat and the correlation with marginal costs is negative.

Zhao (2003) studies a fictitious social planner who maximises the aggregate firm payoffs under two policy regimes - tradable abatement taxes and tradable emission permits setting an industry-wide abatement level. Uncertainty of the permit price leads to stochastic abatement costs. Under both policies, cost uncertainty hampers investments. But tradable permits are preferable over abatement taxes.

van Soest (2005) studies the decision of a single firm to adopt a new energy-efficient technology when its arrival at the markets is not known. Environmental policy is specified as non-tradable quotas and per-unit taxes on the use of energy. In a real options model, he derives the optimal adoption time and finds that the ranking of the policy instruments is ambiguous. If the policy instrument is less strict, the technology will be earlier adopted in the quota regime. If the intensity of the policy instrument increases, the adoption lag is smaller for the tax regime. In Section 3.5 of this thesis, we develop a sequential investment model in which technological progress is not exogenous but a function of the firm's R&D investment efforts. Analysing the impact of the same policy instruments as van Soest (2005), we find that the value to invest increases with uncertainty. The ranking of the policy instruments is also ambiguous in our model. Only if the level of policy stringency is very low are energy taxes the better choice in terms of inducing energy-saving R&D investments. We furthermore analyse a cap-and-trade instrument for the use of energy. This instrument dominates the quota instrument.

Bosetti et al. (2009) perform a simulation of a global climate-economy, which yields the result that investments in energy-efficiency R&D can be higher under a tax policy. But what matters is the way the new technology improves the environmental balance[45]. For example, investments in renewable energies are higher in a cap-and-trade regime.

Concluding, when uncertainty and irreversibility are present neither quality nor quantity instruments lead to first-best allocations. Cost and benefit uncertainties slow down

[43] The economic model describes the development of outputs, capital stocks, and consumption. The climate model computes the concentration of emissions as well as the new temperature. The trend model considers exogenous changes in productivity, population, and the ratio of emissions per output.

[44] Economic uncertainty (labour productivity and consumer preferences) is expressed in a joint likelihood function describing the distribution of historical data (1952-1992 U.S. Worksheets) and exogenous shocks of labour productivity. The development of the likelihood function is conditional on the model parameters, i.e. the probabilities are being up-dated according to a Bayesian rule. Climate uncertainty is modelled by stochastic shocks of the growth rate, climate impacts, control costs and damages, and long-term growth trends.

[45] For further details, see also Subsection 2.3.2, item 5, on optimal environmental policy under uncertain green technological progress.

investments as they create an incentive to wait for the resolution of uncertainties. The situation is different if information can be actively obtained, e.g. by undertaking R&D, thereby resolving technical uncertainty. In this case, investments would be accelerated. The ranking of quantity and quality instruments is ambiguous. The relative advantage of an instrument depends on 1) the relative slopes of marginal benefit and cost functions (if marginal benefits are relatively flat, then price instruments are preferable), 2) the correlation between benefits and costs (if the correlation is negative, price instruments are preferable), and 3) the stringency of the policy instruments. Using realistic parameters, there is a tendency to prefer tradable quotas over non-tradable quotas and quotas over taxes.

2. Intensity of policy instruments under uncertainty

Next, we will summarise contributions that add to a better understanding of the optimal intensity of a policy instrument under uncertainty and irreversibility.

Kolstad (1996) uses a combined economy-climate model. In his global growth model, a social planner maximises the expected net present value of the per-capita utility for a representative consumer. Uncertainty is resolved by learning as time goes by[46] described via a 'news probability vector' of world state variables. This vector is continuously updated according to the learning history. Results of the model are twofold. First, in the absence of climate change irreversibilities (emission stock effects are irreversible), uncertainty and learning about emission stock effects are not the dominating factors. Second, in the presence of uncertainty and learning, irreversible policy costs (sunk capital to control emissions) lead to lower control levels. Kolstad (1996) interprets this finding in two different ways. If learning is fast and hence uncertainty can be resolved quickly, policies should 'go slow' and choose a low intensity of the environmental policy instrument. The second interpretation is that temporary carbon taxes are preferable over permanent taxes.

Ulph and Ulph (1997) explore the relevance of irreversibility in global warming models. In their two-period model, costs about environmental damages are stochastic. Irreversibility of environmental damages implies that the stock of greenhouse gases in the second period cannot fall below a certain fraction of the stock in the first period. They derive a set of criteria for which irreversibility effects should hold. The criteria are tested in an empirical multi-period model. Similar to Kolstad (1996), Ulph and Ulph (1997) find that an anti-irreversibility effect holds in many cases. The abatement level should be lower if more information about damage cost is revealed over time. However, the model also shows that such an effect is absent if the discount rate is low and uncertainty is high.

Fisher and Narain (2003) continue this discussion by introducing endogenous damages from the stock of greenhouse gases (GHG) to the two-period model. This means that the probability of warming and resulting damages are a function of the GHG stock. The scheme of learning about the costs of global warming and the definition of irreversibilities are different from Kolstad (1996) and Ulph and Ulph (1997). Abatement costs are sunk

[46] Kolstad (1996) differentiates between active learning by observation, purchased learning through R&D expenditures, and autonomous learning with passing time (Bayesian learning).

because they are lost for other purposes. Learning in their model is such that the social planner makes observations in the beginning of the second period. A climate event may occur or not, e.g. the global temperature could increase strongly. The social planner can observe if the impact of such an event on abatement costs is low or high. Fisher and Narain (2003) find that the optimal abatement investment in the first period is always higher if uncertainty of environmental damages is endogenous and not exogenous. There are two reasons for this. First, lower risks for global warming yield higher welfare gains. Second, the probability of warming increases in the second period if emissions in the first period are high. A numerical simulation using parameters from the DICE climate model allows the quantification of the role of irreversibilities. The irreversibility effect of sunk investments is substantially larger than that of GHG accumulation.

Wirl (2006) analyses the relationship between global warming caused by burning fossil fuels, uncertainty of the global temperature, and two kinds of irreversibilities (aggregation of CO_2 emissions and stopping CO_2 emissions). A social planner chooses the level of emissions that maximises the sum of expected benefits from burning fossil fuels and expected costs of global warming. There is a critical value for the temperature at which expected costs equal expected benefits. Above this critical value, it is optimal to refrain from all emission. Hence, the social planner will not increase emission levels to trigger an increase in the temperature beyond this value. The lower the chosen emission level, the stricter environmental policies are. Considering an irreversible aggregation of CO_2 emissions, the critical temperature threshold is lower than that of the reversible problem. Considering the option to abandon fossil fuels for some time with the possibility of a later re-introduction (reversible stopping of emissions), the critical temperature threshold is even lower. Similarly, a simulation in Pizer (1999) yields the result that uncertainties raise the optimal level of emission reduction. Half of this effect is caused by the influence of future discount rates. Corresponding welfare gains are about 30 % higher than in the deterministic model.

Baker et al. (2006) develop a two-period model to find the optimal level of global R&D investments under uncertainty of the impact of climate change. They consider different R&D programmes depending on how the global production function is affected, e.g. constant emission reductions, emission cost reductions, and emission reductions proportional to the output level. The optimal R&D strategy resulting from the analytic model is fed into a DICE model. The combined model yields the result that policy is seldom able to hedge against uncertainty. Policies should instead aim to push the probability for a technological advance.

Golub et al. (2009) perform Monte Carlo simulations to study combined exogenous uncertainties, e.g. uncertainty of the feedback of the climatic system, climate sensitivity, and temperature damage costs. They obtain a global distribution for potentially avoided damages and for sunk mitigation costs. Remarkably, costs are not compensated by the benefits. This suggests that the policy target of 450 ppm CO_2 concentration is too strict and not efficient. But the distribution of potential damages has a fat tail implying that catastrophic events are more likely. Therefore, even though a stricter policy target is more expensive, it is connected with lower risks.

Summarising this section, a general result can be noted. Two kinds of irreversibilities are opposing each other - the irreversibility of environmental damages (implying stricter environmental policies) and sunk costs of environmental policy instruments (implying a lower policy intensity). The relative dominance of one and its impact depend on the magnitude of uncertainties, the prospect of learning, and the discount rate. There is a tendency to opt for a higher intensity of present policy instruments if 1) this later on opens up flexibilities, if 2) learning could be accelerated and hence future policies would be better adjustable, and if 3) hedging the risk of a catastrophe compensates inefficiencies of too strict policies.

3. Optimal timing of environmental policy under uncertainty

After presenting an overview of the optimal choice and intensity of pollution control instruments, we now turn to optimal timing problems of environmental policies. An early contribution is Arrow and Fisher (1974). Assuming uncertainty of development and preservation costs, the authors find that an optimal policy hesitance to start an irreversible development, because maintaining flexibility and waiting for more information has a value in itself.

Pindyck (2002) develops a real options model for the optimal timing of a one-time environmental policy with two opposing irreversibilities. First, environmental policy imposes sunk costs on the society. Thus, postponing a regulation is rational. Secondly, immediately acting is of benefit for the environment. The evolution of the pollution stock as well as environmental costs and benefits are uncertain in the model. Pindyck (2002)'s model yields the result that a large uncertainty of benefits increases the option to wait with policy intervention. Furthermore, the smaller the variance in the pollution stock, the higher regrets are in the in case that damages are lower than expected. This 'good news principle' raises the critical value for the amount of pollution above which an environmental policy will be adopted. But the critical value decreases the higher the initial pollution stock is. Lin et al. (2007) extend Pindyck's (2002) model by allowing for correlations between the uncertainties. Furthermore, sunk costs are quadratic. These assumptions increase the critical threshold value in comparison to Pindyck (2002). Hence, policy tends to wait even longer with an intervention. An extension of Pindyck's (2002) model for strategic effects and random technological improvements is published by Ohyama and Tsujimura (2008). If only strategic effects are considered, two competing agents will adopt an environmental policy simultaneously. The critical threshold value for intervention is higher than in the model with only one agent. In the case of uncertain technological progress, incentives to become the first mover exist.

The optimal strategy of a social planner is studied by Baranzini et al. (2003). The sequential investment model takes into account uncertainty in the ratio of benefits and costs associated with global warming. Baranzini et al. (2003) find that the risk of a catastrophe increases the probability of an immediate policy implementation. Furthermore, the lower the discount rate, the earlier environmental policies are adopted.

In sum these studies show that the optimal timing of environmental policy depends on the type of irreversibility. Irreversible environmental damages call for an earlier adoption, whereas sunk costs of policy intervention postpone activities. The time lag closes if the discount rate decreases, if uncertainty is high (low) about environmental damages (policy benefits), and if the correlation between uncertainties is small. Finally, the probability of a catastrophic event shifts the optimal timing towards the present.

4. Impact of policy uncertainty

Environmental policy itself can also be a source of uncertainty. The consequences of this type of uncertainty is the topic of this section.

Larson and Frisvold (1996) explore a firm's investment decision when the polluting input is taxed. In the first period, the firm chooses its optimal amount of factor-augmenting R&D in order to improve its technologies. The first technology utilises a polluting input, whereas the second technology makes use of an environmentally benign input. At the time when the investment choice is made, neither the market prices nor the pollution tax are known. In the second period, the firm observes the realisations of the uncertain quantities. Using this knowledge, the firm now maximises profits from the production with the two inputs, thereby utilising the new factor efficiencies that result from the R&D investments in the first period. The effect of uncertain taxes depends on how new technologies alter the demand for the polluting input in the second period. This issue is complicated as the demand depends recursively on the elasticity of prices. To underline: if tax uncertainty increases, the firm avoids investing if investing implies a lower responsiveness to future price changes.

Farzin and Kort (2000) study the impact of uncertain per-unit emission taxes. When the firm invests in abatement technologies, less emissions per unit of output are produced. The environmental damage is assumed proportional to the output level. The latter is chosen by maximising the net present value of the firm's future cash-flows from producing and/or investing in emission abatement. Farzin and Kort (2000) consider two kinds of policy uncertainty - an uncertain increase in the size of the tax at a certain time (jump to a lower or higher level) and a certain tax increase at an uncertain time. They derive a critical value for the tax rate above which investments always decrease. Below that value tax uncertainty hampers investments compared to the deterministic case. In case of an uncertain size of the emission tax, the model yields the result that investments are accelerated before an expected increase of the tax rate occurs. But at the time when the tax is changed, the level of investment depends on actual tax realisations. If the change in taxes is lower than expected, a lower investment rate is chosen. In case of an uncertain timing of a tax raise, investments are accelerated in order to avoid upcoming higher costs. This effect is stronger the more credible the policy commitment is. Finally, Farzin and Kort (2000) show that the optimal timing problem with an uncertain tax increase cannot be simplified by assuming a certainty-equivalent discount rate.

Baker and Shittu (2006) argue that the results are sensitive to how abatement investments affect the level of emissions. They differentiate between R&D investments into carbon-based technologies and alternative technologies. The latter result in cost reductions, i.e. the price bias between carbon-based technologies and non-carbon based technologies decreases. R&D investments into carbon-based technologies lead to lower emissions per unit of output. Baker and Shittu (2006) study a two-period model. A single firm can produce and perform R&D at the same time. In the first period, the firm chooses the optimal level of its R&D expenditure not knowing the size of taxes. In the second period, after observing the actual tax level, the firm maximises its production. A main result is that R&D efforts do not increase monotonically with an expected carbon tax. R&D investments depend on the elasticity of substitution between non-carbon energy and carbon-energy. If the substitution of elasticity is high enough, R&D into alternative technologies increases. But R&D efforts decrease if both inputs are not good substitutes. For the case that it is optimal to invest in carbon-technologies, investments increase as long as the tax rate is lower than a critical threshold value. Furthermore, Baker and Shittu (2006) find that investment incentives are low if the probability of a high tax is small. The risk of a tax raise expands investments into alternative technologies if the elasticity of substitution is high, and contracts investments if low.

Isik (2004) considers uncertainty of cost-share subsidies studying the impact on the adoption of site-specific technologies. Such technologies are, as an example, relevant for farmers optimising the use of fertilisers. Farmers have the choice between continuing with a conventional technology or investing into the site-specific technology. The investment is irreversible. Related costs and benefits are uncertain. A first finding is that higher cost-share subsidies are needed to compensate the impact of uncertainty. Otherwise, the farmer has an incentive to postpone investments. A second finding is obtained considering policy uncertainty, i.e. the government can switch between a regime granting subsidies and one in which there is no policy support. Investments are best induced if cost-share subsidies are immediately installed and if policy commits to a soon withdrawal.

Summarising this section, uncertainty of policies generally creates an incentive to postpone investments. However, the better a firm is able to realise advantages from investing in abatement measures, the earlier it will invest. The latter is the case if the firm expects a soon withdrawal of cost-share subsidies or an up-coming tightening of environmental taxes or standards. Better adjustment possibilities of the firm, e.g. a high substitutionability of polluting inputs, promote investments in the same way.

5. Optimal environmental policy under uncertain technological progress

Green technological progress in itself is highly uncertain. We will discuss in the following related consequences. A couple of contributions analyse impacts on the social optimal level of environmental R&D and/or abatement investments (Ohyama and Tsujimura, 2008; Baker and Adu-Bonnah, 2008; Bosetti and Tavoni, 2009; Bosetti et al., 2009; Goeschl and Perino, 2009; Blanford, 2009). Optimal technology adoption from the perspective of a firm or a sector is the focus of Chao and Wilson (1993); van Soest (2005); Ansar and Sparks (2009), as well as Fuss (2010) whereas, this thesis explores a firm's R&D activities.

The majority of contributions assume that the technological advance is exogenous leading to direct cost reductions (Baker and Adu-Bonnah, 2008; Bosetti and Tavoni, 2009; Goeschl and Perino, 2009; Blanford, 2009; Fuss, 2010) or efficiency increases (van Soest, 2005; Ohyama and Tsujimura, 2008; Goeschl and Perino, 2009). Chao and Wilson (1993) define technological advance implicitly by assuming a decreasing industry-wide demand for emissions with time. An endogenous approach is undertaken by Ansar and Sparks (2009) and Bosetti and Tavoni (2009) who model the technological progress at an aggregate/global level. An endogenous approach at firm-level is studied in this thesis. Tab. 2.6 gives an overview of the formalisation of uncertain green technological progress in the different contributions.

One of the earliest contributions is Chao and Wilson (1993) who develop a real option model to study the implications of the 1990 U.S. Clean Air Act. Environmental policy sets an annual quota on unscrubbed emissions. Firms have the possibility to buy additional emission allowances or to invest in scrubbers. But the scrubbing capacity is constrained. Chao and Wilson (1993) study the effect of uncertainty of the industry-wide demand for emissions. This demand influences the allowance price and the industry-wide abatement investments. The model yields the result that the market price of emission allowances can be larger than the marginal costs of installing a scrubber, and that this difference can be substantial. It illustrates the flexibility of emission allowances in comparison to the risk of sunk investment costs. Uncertainty of the future demand for emissions lowers investments as it drives the market price of allowances.

As discussed in the previous sections, results can vary depending on the assumed type of a technology. Different types of technologies are explored in Baker and Adu-Bonnah (2008); Blanford (2009); Bosetti and Tavoni (2009), and Goeschl and Perino (2009). Baker and Adu-Bonnah (2008) study how the success probability of an R&D programme[47] influences its optimal amount of funds. Each programme aims to achieve a prior set target for technological change. Progress either directly reduces abatement costs (in the case of alternative technologies) or it reduces the emission-output ratio (in the case of conventional technologies). Baker and Adu-Bonnah (2008) find that programmes for alternative technologies, which are more risky, can require an higher optimal R&D level. This is the case if the probability for severe environmental damages or technological breakthroughs is small. But optimal investments into carbon-technologies are almost independent of the programme risk.[48] This is due to the large share of carbon-based technologies in the markets. Thus, already incremental improvements substantially reduce environmental burdens lowering the programme risk. Therefore, it is important to increase the market share of alternative technologies. However, Baker and Adu-Bonnah (2008) also find that the spread of alternative technologies in the markets is only accelerated if environmental damages are severe. A similar result is found in Blanford (2009). The author performs simulations in an energy-economy model[49] analysing the optimal allocation of investments into three different R&D programmes. He considers performance improvements in the generation of fossil-based electricity, cost reductions

[47]Baker and Adu-Bonnah (2008) capture uncertainty in technological change by allowing for three possible R&D outcomes: a radical breakthrough at which abatement is possible at no costs, an R&D outcome that just meets expectations, and a total failure. The probability at which these outcomes are realised describes the risk of the R&D programme (high risk, low risk).

[48]The robustness of results from the stochastic growth model is checked in a simulation with DICE.

[49]The 'model for evaluating regional and global effects of GHG reduction policies' MERGE is an intertemporal general equilibrium model with 9 macroregions combining top-down elements (neoclassical optimal growth model) and bottom-up elements (specification of energy-input). See Blanford (2009).

Contribution	Description of green technological progress
Implicit modelling	
Chao and Wilson (1993)	industry-wide demand for emissions depends on a random variable; in the case of technological advance, demand decreases
Exogenous arrival	
van Soest and Bulte (2001); van Soest (2005)	energy efficiency parameter following a Poisson process
Ohyama and Tsujimura (2008)	reduction of the cost of environmental policy following a Poisson process
Baker and Adu-Bonnah (2008)	reductions in abatement cost depend on the risk of the R&D programme (as expected, breakthrough, failure)
Bosetti and Tavoni (2009)	reductions in abatement cost of backstop technologies can switch between success or failure
Blanford (2009)	parameterised knowledge production function with optimistic & pessimistic technology paths lowering global abatement costs
Goeschl and Perino (2009)	probability to invent either a backstop technology or a boomerang technology, passive learning included
Fuss (2010)	technology improvements following a Poisson process; decreasing investment costs for non-carbon technologies
Endogenous progress	
Ansar and Sparks (2009)	drift parameter of the technology benefit is linked to the industry-wide adoption rate leading to cost reductions and longer life-time (learning by doing)
Bosetti et al. (2009)	energy R&D increases the stock of knowledge improving global efficiencies & reducing costs (low-tail distributed productivity)
this thesis	learning by performing R&D (Brownian motion)

Table 2.6.: Concepts of modelling green technological progress

of renewable energies, and the viability of CCS technologies. Technological progress is embodied in a parameterised knowledge production function with decreasing returns to scale. The production function depends on technology paths (pessimistic/optimistic), beliefs about future policies, and total budget constraints. Technology paths are derived from expert interviews and are matched to empirical data. Only on the optimistic path are the 'challenging' policy goals achievable. The model also incorporates a lag in the adoption of available technologies. Blanford (2009) finds that the social value of technological progress strongly depends on the market shares of technologies. He concludes that policies should diversify the R&D portfolio in order to account for the characteristics of different technologies.

Bosetti and Tavoni (2009) explore the difference between investments in traditional carbon-free technologies, e.g. fission, and carbon-free backstop technologies, e.g. wind energy. The latter are subject to uncertain R&D outcomes. In the model, a social planner minimises costs to meet a carbon emission target. This is done by choosing the optimal amount of investments into both types of technologies, thereby determining the shares of the technologies in reducing global emissions. Bosetti and Tavoni (2009) find that technological uncertainty leads to higher optimal R&D levels and lower policy costs. Furthermore, conservative non-carbon technologies also play an important role. These technologies are able to hedge downside risks of R&D investments into renewable alternatives. Therefore, given such a backup, R&D programmes can be efficient regardless of high or low success probabilities. In a combined simulation of their model with the climate model WITCH[50], analytic results of the two-period model are confirmed.

Goeschl and Perino (2009) study the interplay between backstop and boomerang technologies. In each period, one of these technologies can be invented. A backstop technology is able to solve all environmental problems. A boomerang technology creates a new type of accumulating pollutant. But boomerang technologies are still connected with an advantage. In the beginning, the new stock of pollutants is zero. The time-continuous stochastic optimisation model is solved in the following way. First, the optimal R&D policy and subsequently the optimal environmental policy are determined. The former equalises marginal benefits of a technology and marginal costs from the technology's stock of pollutants. Environmental policy maximises the social welfare by comparing the benefits of all technologies with environmental damages. The first result is that step-by-step investments are preferable over a strategy that pulls out all resources at once, because boomerang technologies relieve environmental burdens - at least for a while. Therefore, many boomerang technologies can substitute a backstop technology implying that R&D is not anymore driven by environmental concerns. Also note that investments are immediately stopped if a backstop technology is invented. The second result of Goeschl and Perino (2009) is that it is optimal to limit the number of technologies. This calls for reduced R&D rates. The background is that higher rates can accumulate environmental burdens in the future. This is in particular the case if a couple of boomerang technologies have already been discovered. But if the probability of inventing a certain technology type is not known, even a small increase in the expectation to invent a backstop technology accelerates investments significantly. Goeschl and Perino (2009) conclude that the possibility of a breakthrough increases in the case that the government primarily funds basic research. Finally, the society has to except higher equilibrium pollution stocks under the optimal investment strategy. This is a part of the social costs.

Bosetti et al. (2009) compare the optimal amount of energy related R&D investments under a cap-and-trade regime with the optimal choice of an emission tax regime. In the

[50]The World Induced Technical Change Hybrid model WITCH is a combination of top-down elements with bottom-up elements. The model is defined for 12 macroregions of the world. Social planners maximise interdependently the per-capita consumption in their regions by choosing optimal capital stock investments, the R&D expenditure for energy technologies, and the consumption of fossil fuels. The model distinguishes between an electric and a non-electric use of energy. Oil, natural gas, coal, uranium, traditional biomass, and biofuels are the six power-generating technologies. Irreversibility is expressed as a limitation in the substitutionability of the technologies. See Bosetti et al. (2009) for details. Adoption lags are also incorporated.

former, each region receives emission rights. In the tax regime, emissions are subsidised (taxed) if the actual amount of emissions is below (above) the cap set in the cap-and-trade regime. Marginal abatement costs are assumed to be the same world-wide. The simulation with the WITCH model yields the result that investments are higher under the tax policy. Bosetti et al. (2009) also study the dependence of this result on the type of technology. They find that investments in renewable energies are higher in the cap-and-trade regime. Fuss (2010) studies investment decisions in the electricity sector. Investors can invest in fossil power plants (subject to fuel price uncertainty) or in wind farms (subject to an uncertain arrival of technological change). The optimal investment strategy is to postpone investments into wind farms since once investments are sunk, the firm cannot benefit from further cost reductions. Thus, if further cost reductions are expected, the option value of waiting increases. Finally, she finds that technological uncertainty is more important than fuel price uncertainty.

van Soest (2005) studies the influence of energy quotas and taxes on the decision of a firm to adopt an improved technology. The arrival of the new technology is uncertain. The problem is one of an optimal timing solved in a real option model.[51] Environmental policy takes the form of non-tradable quotas and per-unit taxes on the use of energy. The model yields the result that the ranking of the policy instruments is ambiguous. If the policy instrument is more strict, the technology will be earlier adopted in the tax regime. If the intensity of the policy instrument is low, the adoption lag is smaller for the quota regime. The adoption of technologies is also the focus in Ansar and Sparks (2009). They develop a time-continuous real options model based on Hassett and Metcalf (1999). Benefits from the adoption are described as a combined Brownian motion with a Poisson process. The former reflects increasing returns from learning by doing. The latter mimics jumps caused by policy uncertainty or climate catastrophes. Ansar and Sparks (2009) derive that the rate of return that just induces investment (hurdle rate) is high. Indeed, the hurdle rate is always higher than the risk-adjusted discount rate. Ansar and Sparks (2009) argue that this can explain high implicit discount rates for the adoption of new technologies. The hurdle rate is a U-shaped function of the discount rate. For small discount rates, future benefit uncertainty strongly influences today's decisions. This 'markup effect' is connected with high hurdle rates. But when the discount rate slowly increases, the future matters less and the hurdle rate falls. This is reversed when the discount rate reaches some critical value; for discount rates above that value the hurdle rate increases. This is due to the 'basis effect' - discounting requires higher internal rates of return. Finally, Ansar and Sparks (2009) find that if a severe climate catastrophe is likely, the hurdle rate drops significantly.

There is only one contribution studying strategic effects (Ohyama and Tsujimura, 2008). Their model is an extension of Pindyck's (2002) model for the optimal timing of environmental policies (see also the discussion in the previous section). The authors find that the incentive to wait with policy intervention is higher in comparison to the model

[51] The model builds on van Soest and Bulte (2001). Technological advance in that model is factor-augmenting, i.e. a new technology increases the efficiency in the use of energy. Technological uncertainty generates a value of waiting until the efficiency parameter reaches a critical value. The investment lag is a concave function of the mean arrival rate of new technologies.

with only one agent. This is due to the possibility of accelerated investments induced by competition and uncertainty about the technological progress.

Concluding, uncertainty of green technological progress strongly affects optimal investment decisions at firm, sector, and global level, because environmental technologies are connected with higher risks associated with their novelty and low market share. Therefore, environmental policies, which hedge those risks are promising. Examples for such policies are the funding of basic research or the diversification of the social R&D portfolio.

2.4. Chapter summary

Green technological progress stems from eco-innovations of which environmental technologies are a part. The decision to invest in research and development towards green technologies is characterised by the following stylised facts

- The process of R&D and its results are largely uncertain.
- The planning horizon for R&D activities is long.
- Learning is a cumulative process.
- R&D efforts and innovative outputs are significantly correlated.
- R&D investments are largely irreversible.
- Supply-side factors are more relevant for R&D investments than demand-side factors.
- Cost-savings are a main incentive for research activities.

These facts suggest points of departure for the design of theoretical models.

As was illustrated in Section 2.2, there is a need for policy intervention in order to correct market failures caused by knowledge and environmental externalities. The objective of policy instruments is to spur and direct technological progress towards its social optimum. In the environmental-economics literature, uncertainties and irreversibilities are often neglected when evaluating the optimal choice of a policy instrument, as well as that instrument's intensity and timing. Both features have been recognised in financial economics as key issues since the self-amplifying interplay of uncertainty and irreversibility in connection with non-linear functionalities and long-time horizons lead to suboptimal decisions. When studying environmental R&D investment decisions, relevant uncertainties and irreversibilities are those occuring within the stages of innovation, with some uncertainties likely being more relevant in one stage than in another. Earlier stages in the innovation process are more influenced by supply-side factors such as input prices, output prices, policy parameters, technical uncertainty, and market power. In the longer term, sunk costs of investment decisions become the most relevant irreversibilities. Considering these facts and the questions left open from the literature review, we chose to incorporate sunk investment costs and two types of uncertainties, which are technical and policy uncertainty, into the models we will develop in this thesis. In order to reduce the complexity of the problem, our focus is constraint to the investment decision of a single firm.

In Section 2.4.2, we discussed the state of the art in the literature on green technological progress, uncertainty, and environmental policy. The review disclosed that most contributions study the decision problem of a social planner focusing on policy instruments that foster the diffusion of environmental technologies. Much less attention has been paid to the decision problem of a firm undertaking R&D. It is of interest to analyse the extent to which environmental policy instruments can provide incentives for green R&D investments. In addition, while most contributions consider ecological and market uncertainties, such as uncertainty of environmental impacts and uncertainty of costs and benefits, there is a lack of models exploring the consequences of regulatory uncertainty and uncertainty of the technological progress, particularly when the progress is not exogenous (see Tables 2.5 and 2.6). To our knowledge, there is no contribution combining both uncertainties. Regarding formal issues, the majority of models are restricted to the analysis of two time periods.

Moving foreward from the existing literature, we will focus on R&D investment decisions from the perspective of a single firm. The first step will take account of technical uncertainty endogenous to the firm. In a second step, we explore how additional uncertainty of environmental policies affects the optimal R&D investment decision. A suitable approach to incorporate these features is the theory of real options. In our implementation of this theory, we will develop continuous-time sequential investment models going beyond two-period descriptions.

3. R&D investment under technical uncertainty

3.1. Concept and formalisation of technical uncertainty

Research and development projects are not one-time investments but take time and may run several months or years. They require repeated investments, e.g. to pay researchers for their work or to purchase and maintain installations, equipment, and devices. This sequential character of R&D investments allows for different kinds of managerial flexibilities and creates option values.

In order to keep the option of continuing the project open, it is usually necessary to proceed at least with a minimum investment rate. For example, researchers may be contracted to receive guaranteed payments even if the R&D project is put on the back burner. R&D projects are also characterised by a high degree of irreversibility. If the project is abandoned, a large share of investments will be lost. Examples for such sunk costs includes researchers moving to other projects or R&D equipment which is too specific to be re-used for other purposes.

The fourth feature of R&D projects is that they involve substantial uncertainty over future developments. This results in an unknown evolution of input factor and output factor costs. As distinguished from other sequential investment projects, uncertainty connected with the scientific progress is particularly important to R&D projects. It is difficult to predict if a project will be successful, or from a more optimistic point of view, how much time and expenditure are needed in order to achieve the desired research goals. Following Pindyck (1993), we will call this type of uncertainty *technical uncertainty.*[1]

Technical uncertainty can be resolved by undertaking an R&D project. Step by step, the firm learns about the project and its success or failure probability. As this type of uncertainty is specific to a single project, it is endogenous to the firm and thus independent from environmental or market conditions. Therefore, technical uncertainty cannot be eliminated through diversification.

The reduction of technical uncertainty at each investment step lowers uncertainty about the remaining investments required to complete the project. Hence, this type of uncertainty creates a shadow value of the R&D project which makes the investment

[1] Note that in the literature often two terms, *technical* and *technological* uncertainty, are used interchangeably. However, these are two different kinds of uncertainties that should not be confused. One is associated with uncertainty in a single project. The other describes an industry-wide uncertainty, e.g. uncertainty about the availability of specific technologies in the future. Hence, Oriani and Sobrero (2008) suggest to name the former *technical* uncertainty and the latter *technological* uncertainty.

more attractive. To illustrate this feature of technical uncertainty, consider the following simple example of a project with a one-time possibility to review the investment decision. For simplicity, we refrain from discounting future cash-flows.

Let us consider a firm that plans an initial investment of 0.5 Million EUR in order to improve the efficiency of a portable device for energy storage. After half a year the firm will review the development progress. There is a 50% chance that the project will be finalised by that time. However, time could also reveal bad news making the investment of another 1.6 Million EUR necessary. Suppose the firm expects total profits of 1.2 Million EUR selling the improved devices. From a classical point of view, it is not rational to invest at all as expected investment costs exceed expected profits and the resulting Net Profit Value is negative, i.e. 1.2 MEUR - (0.5 MEUR + 0.5*1.6 MEUR) = -0.1 MEUR. However, with the option to abandon, the firm has the flexibility to review the project and decide about its continuation. After the first investment stage, the value of continuing the project is -0.5 MEUR + 0.5*1.2 MEUR = 0.1 MEUR. Therefore, in hindsight the possibility to abandon, it would have been rational to have started with the first investment step. Thus, even if the classical Net Profit Value is negative, it might be rational to start an investment project that involves technical uncertainty. Classical valuation methods, such as the Net Profit Value Method (NPV), neglect the possibility to abandon the project when bad news occurs.

Technical uncertainty can be formalised using stochastic processes[2]. Sudden knowledge breakthroughs can be described by Poisson processes - the economic quantity depending on technical uncertainty will jump with a certain probability to a lower or higher level. For example, Berk et al. (2004) use a Poisson process to describe an incremental technical progress by assigning a success probability to infinitesimal research stages. The firm's R&D productivity is thereby depending on the number of completed stages and the cumulative amount of time spent investing. Thus, technical learning is based on previous success.

Another possibility is to model technical uncertainty with controlled diffusion processes[3] whose increments fluctuate around a trend. We follow Pindyck (1993) by analysing the effect of technical uncertainty on the expected remaining investments required to complete the project. This expenditure is a cumulative quantity denoted with $K(t)$ and measured in units of a numéraire. Thus, the total cost to completion is a stochastic variable $\tilde{K}$ and $K = \mathcal{E}(\tilde{K})$. In the trend, the expected cost to completion $K(t)$ decline as investments proceed with investment rate $I(t)$. When K reaches zero, the project is finalised, i.e. $K(T) = 0$ with T being the time needed to complete the project. Infinitesimal changes in K are given by a stochastic differential equation

$$dK(t) = -I(t)dt + g(I,K)\,dw(t) \quad . \tag{3.1}$$

A continuous decrease of $K(t)$ is described by the first term of Eq. (3.1), the drift

[2] See Appendix A.1 for a basic introduction of essential terms.

[3] Diffusion processes are continuous time parameter stochastic processes which possess the strong Markov property and for which the sample paths $X(t)$ are almost always continuous functions of time t. This means it is relatively unlikely that large displacements occur in ϵ-small time intervals. See e.g. Karlin and Taylor (1981, Chap. 15) for a definition and properties.

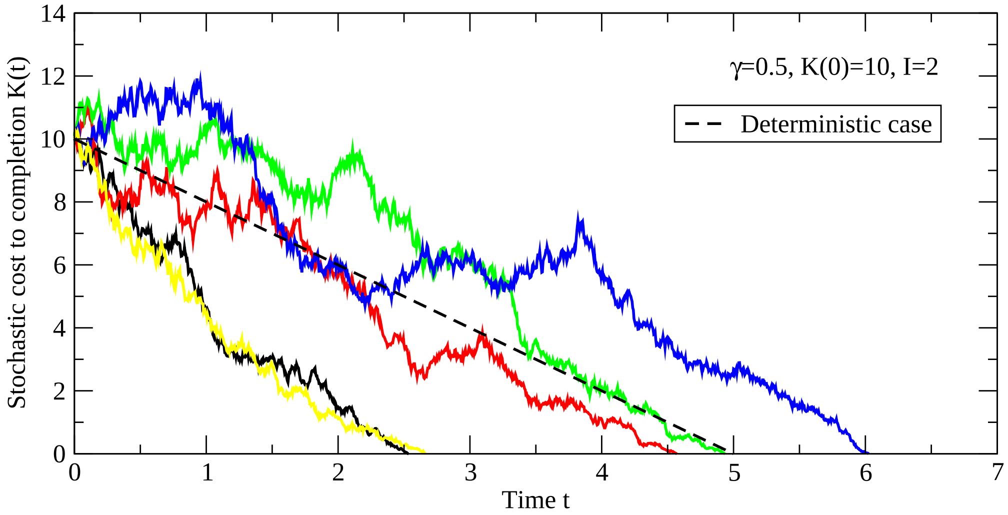


Figure 3.1.: Realisations of expected investment cost to completion $K(t)$.

term. Fluctuations around this trend are modelled by the second term, the diffusion term. Its stochastic increments $dw(t)$ are those of a Wiener process[4] $w(t)$. They are independent of each other and their variance grows linearly with time. The Wiener process is assumed to be idiosyncratic, i.e. uncorrelated with the economic environment. The expected remaining expenditure $K(t)$ required to complete the project can also be understood as a monetary valuation of ignorance that is being reduced with investments $I(t)$. Fluctuations around the trendline are thus unexpected knowledge increments (below the trendline) or unexpected backlashes (above the trendline).

Regarding the function $g(I, K)$, the following assumptions are made. $g(0, K) = 0$, i.e. without investments, the expected cost to completion does not change as no new knowledge will be revealed. Accordingly, the rate of investment $I(t)$ controls Eq. (3.1). $g(I, K)$ also needs to satisfy $\partial g/\partial I > 0$, i.e. an increase of K implies that the progress was slower than expected. In addition, the variance of the expected cost to completion decreases with K, and the actual total cost will only be known for certain once the project is finalised. A common specification of $g(I, K)$ satisfying these assumptions is

$$g(I, K) = \gamma \sqrt{I(t)K(t)} \ , \tag{3.2}$$

where γ is a constant, positive parameter depicting the overall technical uncertainty. In Fig. 3.1, samples of the evolution of $K(t)$ according to Eq. (3.1) with specification Eq. (3.2) are shown.[5] We assume initial cost of $K(0) = 10$, a constant investment rate of $I = 2$, and technical uncertainty $\gamma = 0.5$. In a world of certainty, it would take

[4] A Wiener process obeys $dw = \zeta_t\sqrt{dt}$ where ζ_t is a normally distributed random variable with zero mean and unit standard deviation. See also Fig. 3.2 (right-hand part). Thus, the expectation value of w is $\mathcal{E}(dw) = 0$ and its variance is $\mathcal{V}ar[dw] = \mathcal{E}((dw)^2) = dt$.

[5] Stochastic paths are created in a simulation solving the stochastic differential equation Eq. (3.1) with the Euler-Maruyama method. Δt was chosen as 10^{-5}.

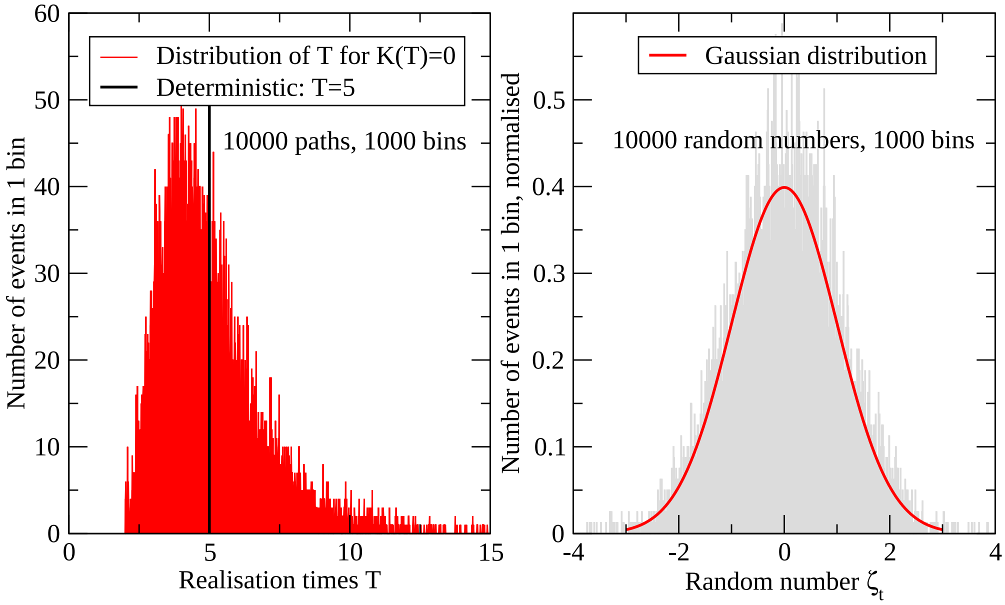


Figure 3.2.: Distribution of realisation times T, left, and distribution of random number ξ_t of the Wiener Process, right.

five investment steps to reduce the initial cost to zero. However, with uncertainty, the path of remaining investments required to complete the project fluctuates. Therefore, the completion time T is scattered around the deterministic realisation time $T = 5$, yet not normally distributed. This is shown in the left-hand part of Fig. 3.2. The 10000 simulated paths with their realisation times T have been sorted into 1000 bins of equal length. On the contrary, the random number ζ_t of the Wiener process in Eq. (3.1) is normally distributed (see the right-hand part of Fig. 3.2). In this figure, 10000 random numbers are simulated and their distribution is plotted together with the standard normal distribution.

Eq. (3.2) furthermore implies that the instantaneous variance of dK/K increases linearly with I/K. The longer investments have been undertaken, the lower the likelihood for surprises. The latter is not the case in early phases of the project when K is high. This can also be seen from the sample paths in Fig. 3.1. The variance of the actual total cost $\tilde{K}$ can be derived analytically as

$$\mathcal{V}ar(\tilde{K}) = \frac{\gamma^2}{2-\gamma^2}\, K^2 \quad \text{and} \quad \gamma < \sqrt{2} \;, \tag{3.3}$$

for details see the Appendix A.3.1. To bring in the feature of R&D projects that technical uncertainty is larger in earlier stages of the R&D project, Kort (1998) modifies Eq. (3.2) by introducing an additional constant parameter $\delta > 0$. Then, $g(I, K)$ takes the form

$$g(I, K) = \gamma\, K(t)^{\delta} \sqrt{I(t)K(t)} \;. \tag{3.4}$$

We will use both specifications later on.

3.2. Review of real options literature on R&D investments

A suitable approach to evaluate sequential research and development projects under uncertainty is to study real option R&D models. We will briefly review the main findings of this literature. There, capital investment decisions (real options) are treated similarly to financial options, i.e. knowledge is seen as a strategic asset that is of value and includes executable options. These business options contribute to the value of a project which is not simply quantifiable as it depends on principally unknown future developments. Of main interest is how technical and/or market uncertainty affects the value of investment projects. In a recent review paper, Newton et al. (2004) divide research on real R&D options into ten primary, partly overlapping lines: general R&D planning, planning R&D in stages, testing, the timing of new product developments, operations, abandonment, risk sharing, market funding, industry strategy, and regulations. In this thesis, research is concerned with R&D planning, timing, and the influence of policy regulations under technical uncertainty that can be resolved by investing in in-house research projects.[6]

Real option models draw substantially from the seminal works of McDonald and Siegel (1986), Majd and Pindyck (1987), and Pindyck (1993).[7] McDonald and Siegel (1986) and Majd and Pindyck (1987) study sequential investment projects with stochastic benefits from the project and stochastic investment cost. With the investor having the choice between waiting or investing, the optimal strategy depends on a critical threshold for the expected cost to complete the project. While these models do not include technical risks, Pindyck (1993) develops a sequential investment model under technical and input cost uncertainty. The basic finding is that the value of the investment opportunity increases with technical uncertainty, whereas input cost uncertainty depresses investments.[8] These models have been applied to various investment decision problems, most often to pharmaceutical R&D and natural-resource utilisation such as the optimal exploitation of oil fields or mines. Recent books on these applications are, e.g., Brennan and Trigeorgis (2000) and Paxson (2003).

Schwartz and Moon (2000) study four phases in the development of new drugs, considering uncertainty about investment costs, future payoffs, and the possibility of a catastrophic event able to terminate the project. They derive critical asset values for each phase and analyse the dependence of these values on types of uncertainty (technical uncertainty, asset value uncertainty) and model parameters. They find that uncertainty

[6] There is another broad line of research exploring capital investment decisions when new technologies are *exogenous* to the firm, i.e. technologies arrive at a random date for purchase at markets. Applications in environmental-economics are Chao and Wilson (1993); van Soest and Bulte (2001); van Soest (2005); Ansar and Sparks (2009); Fuss (2010). See Section 2.3.2 for a discussion.

[7] A classical book on investment under uncertainty is Dixit and Pindyck (1994).

[8] In a time-continuous stochastic control model, Grossman and Shapiro (1986) determine optimal R&D investment paths of a single firm when either the amount of progress is not known or there is a stochastic relationship between effort and progress. They find that the prospect of more information about a well running project accelerates investment efforts. If the progress is exogenous and smaller than expected, the firm might instead scale down or stop the project. If otherwise, the progress depends on the firm's efforts: bad news leaves the rate of investment unchanged. Thus, uncertainty in R&D expenses results in favouring risky projects even if the return after completion does not increase.

always increases the project value. However, the value of investment opportunity depends positively on the asset value and negatively on expected costs. Uncertainty in expected costs (modelled as technical uncertainty) lowers the critical value of the option to invest as investments reveal information. On the other hand, uncertainty in the asset value does not improve investment conditions.

Common to the aforementioned models is the treatment of investment projects as American call options, i.e. the investor has the right to decide at any time about continuing or abandoning the investment. However, closed-form solutions of American call options are generally not known, instead one relies on numerical solutions or simulations. The latter transfer an American call option to 'exotic' options leading to discrete rather than of time-continuous models. Schwartz (2004) solves a sequential investment model for patent protected R&D projects by simulation. He considers cash-flow uncertainty, uncertainty in the cost-to-completion, and the possibility of catastrophic events. The option of abandoning the project contributes significantly to the project value if uncertainty is high. Lint and Pennings (2003) among others[9] relax the assumption that volatilities are the same throughout the project. They separate R&D into distinct phases, i.e. a research phase, a development phase, and a start-up phase. Each of these phases have a different underlying characteristic and have to be passed successfully before entering the next stage. Errais and Sadowsky (2008) study a model in which investment costs are a function of uncertainty and remaining stages. They find that learning in earlier phases has a crucial effect. In a different approach, Kort (1998) explores the influence of higher uncertainty in the earlier phases of an R&D project and also confirms the importance of this feature.

Mölls and Schild (2006) deal with the role of a corridor for the investment rate instead of the usual choice between zero-investment and investment with a maximum rate. A result is that a marginal increase of the lower boundary for the investment rate creates further incentives to invest with maximum efforts. The effect of an 'initial euphoria' (Bar-Illan and Strange, 1998) still exists, but the enthusiasm is lower, if a minimum investment rate is introduced. Multiple R&D projects are studied by Childs and Triantis (1999). Under these conditions, the optimal research policy for a single firm is to foster a lead project, whereas other projects are just kept alive as 'back-ups'. However, if competition is introduced, the firm prefers to run projects in parallel. The analysis of strategic options under competition is a research area of recent interest. By considering research spillovers, game theoretic analysis is combined with real options theory, see Kulatilaka and Perotti (1998) among others. For example, Lukach et al. (2007) develop a two-stage R&D model with technical uncertainty and strategic actions. They focus on welfare implications, e.g. effects on the cost-efficiency of new technologies, generating ambiguous results.

In real options models, technology policy typically enters the decision problem in form of R&D subsidies or taxes. Supply-side support (technology-push policy) backs up R&D investment costs and hedges technical risks. Demand-side support (market-pull policy) aims to bolster returns from developing new technologies and to facilitate market access. As reviewed in Section 3.3.2, the impact of environmental policy on sequential investment

[9] See e.g. the review in Newton et al. (2004).

decisions of a firm undertaking R&D has gained little attention so far. In the remaining chapters of this thesis, we will explore such kinds of models. Next, however, we will study Pindyck's (1993) model with technical uncertainty in detail to supply the basic background and provide the benchmark for following analysis. This model is extended and applied to R&D investments in offshore wind parks including feed-in tariffs (Section 4.4). Section 4.5 explores R&D decisions for energy-efficient technologies under energy taxes, energy quotas, research grants, and emission trading. Chapter 5 additionally introduces uncertainty about environmental policy into the investment problem.

3.3. The basic model and its solution

In this section, we discuss Pindyck's (1993) basic model to solve a sequential investment problem under irreversibility and technical uncertainty.

Consider a firm planning to self-finance an R&D project that requires time to be completed. The project can only be realised if all investment stages are passed successfully. Thus, the firm holds a sequential call option. We assume that the major source of uncertainty is a technical one, expressed by the fact that the firm can only make a projection about the time required and total remaining expenditure needed to complete the project. Remaining investment costs to completion decline with a trend controlled by the firm's investment rate and fluctuate around the trend due to technical uncertainty. Actual investment cost will only be known for certain once remaining cost to completion has reached zero (for more details see Section 4.1). After the finalisation of the project, the firm receives cash-flows that are assumed to be known for certain. The model is a continuous-time model, i.e. the firm reviews its investment decisions constantly and can abandon the project at any time if the progress is not satisfying. However, once the project has been stopped, investments are lost and re-investment is not possible (irreversibility feature). For simplicity, we neglect additional costs that are incurred if the project is abandoned (this does not change the general results).

We will denote the expected cost to completion by $K(t)$. Actual total cost $\tilde{K}(t)$ are stochastic. Thus, $K(t) = \mathcal{E}(\tilde{K}(t))$ where $\mathcal{E}$ is the expectation-value operator. $K(T)$ vanishes if the project is completed. T is the actual, stochastic completion time. The evolution of the expected cost to completion $K(t)$ is modelled by the stochastic equation

$$dK(t) = -I(t)dt + \gamma\sqrt{I(t)K(t)}dw(t) \ , \tag{3.5}$$

$I(t)$ being the investment rate at time t and $dw(t)$ the increment of a Wiener process. The constant parameter $\gamma > 0$ describes overall technical uncertainty. We assume that there is a maximum investment rate $I_{\max}$ at which the firm can productively invest (feature 'time to build'). Thus,

$$0 \leq I(t) \leq I_{\max} \ . \tag{3.6}$$

Now we can formulate the firm's stochastic control problem. Controlling the flow of investments $I(t)$, the firm aims to maximise the value of the investment opportunity.

Introducing a discount rate r, this value is given by a function F as

$$
\begin{aligned}
F(K(t)) &= \max_{I(t)} \mathcal{E}_0 \left[\int_T^\infty P \exp(-rt)dt - \int_0^T I(t)\exp(-rt)dt \right] \\
&= \max_{I(t)} \mathcal{E}_0 \left[\frac{P}{r} \exp(-rT) - \int_0^T I(t)\exp(-rt)dt \right] \quad , \qquad (3.7)
\end{aligned}
$$

also called the value-function of the decision problem.[10] The first term describes the discounted cash-flows after completing the project, whereby P is the constant cash-flow per period. In sum, the firm will hold an asset worth $V = P/r$. The second term describes the sum of investments needed to complete the project. The problem is stochastic due to the stochastic completion time T. Therefore, the expectation operator for the initial decision at time $t = 0$, $\mathcal{E}_0$, rules the development of future net profits. Eq. (3.7) is subject to the constraint of a maximum productive investment rate $I_{\max}$, Eq. (3.6), and $K(T) = 0$. The evolution of $K(t)$ is given by Eq. (3.5).

The solution of Eq. (3.7) serves as a toolbox for the firm to decide if the investment in the R&D project is profitable. It determines the optimal investment rate $I(t)$ for each moment of time maximising the value function $F(K(t))$. Note that the value function $F(K(t))$ is positive for all $K(t)$. It is even strictly positive for all t if $I(t) > 0$. But $F(K(t))$ is zero if it is optimal not to start with investments or to abandon the project midstream. Furthermore, $F(K(t))$ has the same structure for all t and depends only on the starting value of $K(t)$.

The stochastic control problem can be solved by different methods, see e.g. Spall (2003) for an overview. In the following sections, we will solve the model by means of standard dynamic programming techniques and by Monte Carlo simulation.

For the case of certainty ($\gamma = 0$) it is straightforward to obtain the following solution.[11] Investment with the maximum investment rate is optimal as long as the expected cost to completion K are smaller than a critical threshold K^* which is

$$
K^* = \frac{I_{\max}}{r} \ln\left(1 + r\frac{V}{I_{\max}}\right) \quad . \qquad (3.8)
$$

3.3.1. Solution by dynamic programming

The rationale for the solution of stochastic control problems via dynamic programming is based on Bellman's principle of optimality stating

> *An optimal policy has the property that, whatever the initial state and initial decisions are, the remaining decisions must constitute an optimal policy with regard to the state resulting from the first decision (Bather, 2000, p. 18 ff).*

[10] $F(K(t))$ is a short notation for $F(K(t); I(t), P)$. $I(t)$ can be dropped as it controls $K(t)$.
[11] The critical threshold K^* for the cost to completion is obtained by solving Eq. (3.7) for $F(K^*) = 0$.

The intent of Bellman's principle is to split the problem into smaller sub-problems. The general solution is found in a backward recursion.[12] The application of this principle defines the Bellman equation for the value function $F(K(t))$

$$rF(K(t)) = \max_{I(t)} \left\{ -I(t) + \frac{1}{dt}\mathcal{E}_0[dF] \right\} \ . \tag{3.9}$$

The interpretation of this equation is as follows. The left-hand side expresses the discounted value of the investment opportunity. This value attains its maximum if the sum of immediate payments and expected total returns per unit time from holding the investment opportunity is maximised (right-hand side).

Eq. (3.9) can be further evaluated using stochastic calculus. First, we apply Ito's Lemma[13] to derive an expression for infinitesimal changes of F. We obtain

$$dF(K) = -I\frac{\partial F}{\partial K}dt + \frac{1}{2}\gamma^2 IK\frac{\partial^2 F}{\partial K^2}dt + \gamma\sqrt{IK}\frac{\partial F}{\partial K}d\omega \ . \tag{3.10}$$

Next, we expand this expression using a Taylor series and execute the expectation-value operator. Being interested in the derivative, we truncate after the linear terms in dt. Doing so (and suppressing time arguments for simplicity), we get up to order dt^2

$$\begin{aligned} \mathcal{E}[dF] &= \mathcal{E}[F(K+\Delta K, I+\Delta I|K, I) - F(K, I)] \\ &\approx -\left(I\frac{\partial F}{\partial K} + \frac{\gamma^2}{2}IK\frac{\partial^2 F}{\partial K^2} \right) dt + O(dt^2) \ . \end{aligned} \tag{3.11}$$

Note, Δ is the difference operator and O denotes the order of approximation in Landau notation. Inserting this expression into the Bellman equation, Eq. (3.9), gives

$$rF(K(t)) = \max_{I(t)} \left\{ -I(t) - I(t)\frac{\partial F(t)}{\partial K(t)} + \frac{\gamma^2}{2}I(t)K(t)\frac{\partial^2 F(t)}{\partial K^2(t)} \right\} \ . \tag{3.12}$$

As this equation is linear in $I(t)$, the maximisation can be executed and a first important result can be obtained: it is optimal to invest either at the maximum investment rate $I_{\max}$ or not at all (bang-bang solution). Note that this simple investment policy also holds if $K(t)$ is not only subject to technical uncertainty but depends additionally on input cost uncertainty correlated with the economy (see Pindyck (1993)). However, the rule does not hold if $K(t)$ and the project value $V(t)$ are subject to uncertainty *and* if these processes are correlated (see e.g. Schwartz (2004)).

Eq. (3.12) has a free boundary K^* that separates an investment region from a non-investment region. If the expected remaining costs to completion K are smaller than

[12] This depends on the class of stochastic processes involved. Diffusion processes belong to the class of Markov processes. A fundamental property of Markov processes is that future developments can be separated from the past ones conditional on the initial stage. The consequence is that the probability distribution of some x_{t+1} can be described by x_t and by a decision variable a_t (Lagrangian $L(x_{t+1}|x_t, a_t, t)$).

[13] Ito's Lemma gives the differential of stochastic processes $dx = a(x,t)dt + b(x,t)dz_t$ as $dF(x;t) = \frac{\partial F}{\partial t}dt + \frac{\partial F}{\partial x}dx + \frac{1}{2}\frac{\partial^2 F}{\partial x^2}(dx)^2$. See e.g. Pindyck (1993, Chap. 3).

K^*, the firm will invest. If $K > K^*$, it is optimal to refrain from investment. Good (as well as bad) surprises are not likely to induce large displacements of K. Thus, there is a critical value which can not be pushed by the stochastic nature of the model however promising the news might be. The optimal investment rule is thus

$$I(t) \quad = \quad \begin{cases} I_{\max} & \text{if} \quad K < K^* \ , \\ 0 & \text{if} \quad K > K^* \ . \end{cases} \tag{3.13}$$

The free boundary $K^*(t)$ satisfies two boundary conditions for all t, the value-matching condition and the smooth-pasting condition

$$F(K^*(t)) = 0 \ , \quad F'(K^*(t)) = 0 \ . \tag{3.14}$$

The first condition ensures that the border values of the value function $F(K(t))$ in the investment region and the non-investment region match. The second condition ensures that this is done smoothly, i.e. the values meet tangentially at the boundary (see Pindyck (1993) for details).

Moreover, it holds that

$$F(0) = V \ , \quad \lim_{K \to \infty} F(K) = 0 \ . \tag{3.15}$$

The first equation describes the payoff from the project once it is completed. The second condition states that it is not reasonable to start the project at all if $K(t)$ is tending to infinity as the value function F for the investment opportunity approaches zero.

Next, the free boundary K^* has to be calculated. For $K < K^*$, Eq. (3.12) is a second-order ordinary differential equation that can be solved by eliminating its singularity at $K = 0$ with the substitution $K = \exp(x)$ for $I \neq 0$ (see Appendix A.3.2 for details). This transforms Eq. (3.12) into a system of coupled first-order differential equations, Eqs. (A.10), a system of equations that can be solved numerically by standard shooting methods. We use a Runge-Kutta-Merson method. The programme code is included as Appendix A.3.3. Numerical results and comparative statistics for the basic model are discussed in Section 3.3.3. First, we explain how to solve the model by a Monte Carlo simulation.

3.3.2. Solution by the Monte Carlo method

The idea of the Monte Carlo approach is to simulate many random paths of $K(t)$ and to derive the optimal investment policy in a backward recursion for each path. The value function $F(t)$ can then be calculated averaging variables that define the optimal evolution. By this method, the time-continuous investment model is replaced by a discrete investment model.

The solution procedure starts with the creation of n stochastic paths for $K(t)$ conditional on investing at the maximum investment rate $I_{\max}$. Stochastic Eq. (3.5) is then solved by the Euler-Maruyama method.[14] This method makes a discrete approximation

[14] An excellent introduction to algorithms for simulating stochastic differential equations is Higham (2001).

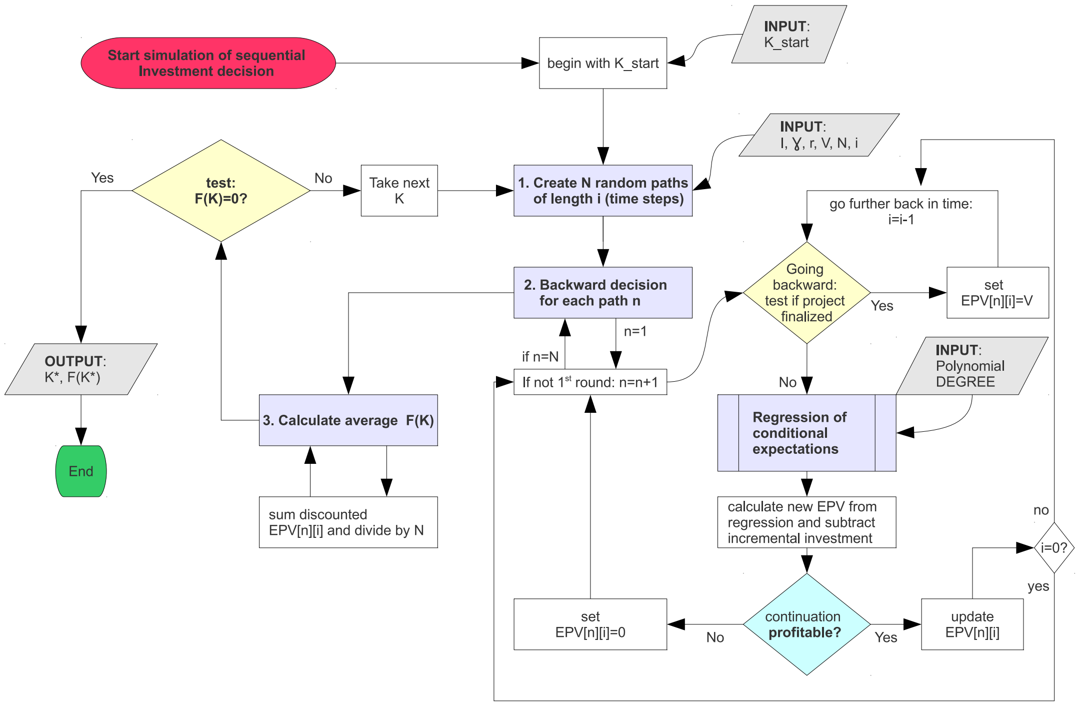


Figure 3.3.: Flow chart of the Monte Carlo code to solve the basic sequential investment model under technical uncertainty.

of the time-continuous evolution. Expected cost to completion K at a point in time i and for path n take the form of a matrix equation

$$K_n[i] = K_n[i-1] - I_{\max} dt + \gamma \sqrt{I_{\max}\, K_n[i-1]}\, dw[i] \ . \tag{3.16}$$

The size of dt is given by $dt = t_{\text{sim}}/m$, with t_{sim} being the total simulation time and m the total number of time steps. The stochastic increment is simulated as $dw[i] = \zeta[i]\sqrt{dt}$ where $\zeta[i]$ is a vector of normally distributed random variables.[15] Note that $K_n[i]$ is filled with zeros for all i once K_n has been reduced to zero. Fig. 3.1 illustrates some example paths for $\gamma = 0.5$, $K(0) = 10$, $I_{\max} = 2$, $t_{\text{sim}} = 50$, and $m = 10000$. The simulation procedure is illustrated in the flow chart Fig. 3.3.

Following the generation of n random paths, the optimal investment policy is derived in a backward recursion for each path. The decision in each time step i to continue or to stop investments is conditional on the fact that the project will not be abandoned in $i + 1$.[16] This choice is made by calculating the net expected values of the project

[15] Standard distributed random numbers can be created using the Box-Muller algorithm, $\zeta[i] = \sqrt{-2\ \ln(u)}\, sin(2\pi\, v)$ where u and v are computer generated, uniformly distributed random numbers. In our simulations, the pseudo random number generator srand() has been used for this purpose.

[16] This decision has already been made as we are going backward in time.

in time step i. If this value is positive, continuation is optimal. Otherwise, the project will be abandoned. The procedure begins at $T = m * dt$. This is the time when the project is finalised, i.e. $K_n[T] = 0$. At this point, the conditional expected project value $EPV_n[T]$ is known for certain and always positive as the firm can retrieve an asset of value V. However, one step back in time things could look different because an infinitesimal investment of $I_{\max}dt$ still would be needed to complete the project and it is the *net* expected conditional project value that is relevant for the decision at time step $i - 1$.[17] When the optimal investment rule in a time step i is found, the stepping-back procedure is repeated until the initial time is reached[18]. This is done for all paths.

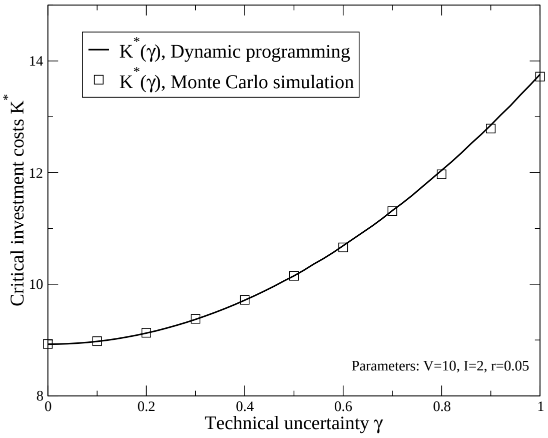
The challenge is to calculate expected conditional project values if investments are not finished and uncertainty has not completely been resolved. A first idea might be to use the discounted project value of one period ahead in time. However, this underestimates the complex role of uncertainty and leads to a bias towards the proper solution of Eq. (3.7). In this way not every dependency on all paths and decision times will be taken into account. A more practical approximation of expected conditional project values has been proposed in Longstaff and Schwartz (2001) who regress discounted expected project values of the next period $EPV_n[i+1]$ by the expected cost to completion for the current period $K_n[i]$ for all not abandoned paths. There are different possibilities to specify basis functions for this regression. For our simulation, we apply the Longstaff-Schwartz method using a polynomial regression of degree 5.

After having approximated the conditional expected project values, we test for each i going backward in time if the net values are positive, i.e. the necessary incremental investment $I_{\max}dt$ in i does not exceed the regressed $EPV_n[i]$. Otherwise $EPV_n[i]$ is set to zero. When the initial time is reached, the optimal investment policy for each path will have been determined by this method. The value function $F(K)$ can then be calculated by adding up discounted $EPV_n[i]$ and averaging over all paths. The critical threshold K^* for the investment cost to completion can be found by increasing initial costs to completion $K_n[0]$ until it is optimal to abandon investments for *all* paths in the project.

Fig. 3.4 compares the solution for K^* in dependence of γ obtained by dynamic programming and by Monte Carlo simulation. The later was run with 10000 paths and 30000 time steps in a total simulation time of $t_{\text{sim}} = 10$. Both approaches match and replicate results of Dixit and Pindyck (1994, p. 350). The table to the right shows the growing number of abandoned paths when $K_n[0]$ approaches K^*. For example, when $K_n[0]$ reaches the deterministic critical threshold for the cost to completion of about $K^* \approx 9$, only 2049 paths out of 10000 are abandoned at $\gamma = 0.5$. Fig. A.1 (Appendix A.3.4) depicts how the completion times for these abandoned paths are distributed (upper graph). Their mean completion time is $< T >= 5.7$ with a standard deviation $\sigma = 1.8$. The lower graph of Fig. A.1 shows the distribution of the times at which the decision to

[17] Note that the probability to abandon the project in later time steps is much smaller than in earlier time steps as strong fluctuations of K are rather unlikely.

[18] Taking the backward-decision only at the finalisation time of the project corresponds to a European rather than an American option. The latter allows one to execute the option to abandon the project at any time.



K	F(K)	Paths stopped
	$\gamma = 0.5$	
10.12	0.04	8963
10.13	0.03	9165
10.14	0.02	9380
10.15	0.00	10000
	$\gamma = 0.7$	
11.23	0.032	9262
11.24	0.027	9380
11.25	0.026	9478
11.26	0.000	10000

Figure 3.4.: Comparison of the free boundary K^* obtained by dynamic programming and by Monte Carlo simulation (left). The table to the right shows the number of abandoned paths when K^* is approached.

stop these investment paths are made. 87% of the paths are abandoned within the first quarter of the total simulation time. The mean time of abandoning is $< T >= 1.2$ with standard deviation $\sigma = 1.1$.

While this kind of statistical information cannot be revealed by dynamic programming, its advantage is that the numerical error is very small at short running times (up to four decimal places within seconds). In contrast, the accuracy of the Monte Carlo simulation has to be bought at the cost of long code run times as the normal distribution is realised by a finite set of N random numbers according to $\sqrt{N}$. Thus, increasing the accuracy by one digit requires the increase of the sample by a factor of 100. The other important parameter in the simulation is dt. Only for $dt \to 0$ does the time-discrete solution converge to the solution of the continuous-time model.[19] Finally, there is a numerical error resulting from the regression of conditional expected project values. This is, however, small in comparison to the approximations discussed before.

3.3.3. Results and comparative statistics

The solution of Eq. (3.7) yields a basic finding: technical uncertainty raises the critical cost to completion and thus expands the investment region. Investments are rewarded with information about the success or failure probability of the R&D project creating a shadow value, in addition to the direct value, in completing the project. Fig. 3.5 shows the dependence of the critical costs to completion from parameters of the basic model. These are the technical uncertainty γ, the discount rate r, the maximum investment rate $I_{\max}$, and the payoff after completion V.

The numerical example for the graphs is chosen as in Dixit and Pindyck (1994). The project is assumed to be worth $V = 10$. Thus, a discount rate of $r = 5\%$ and a maximum

[19] This corresponds to the difference between an American and the corresponding Bermuda option.

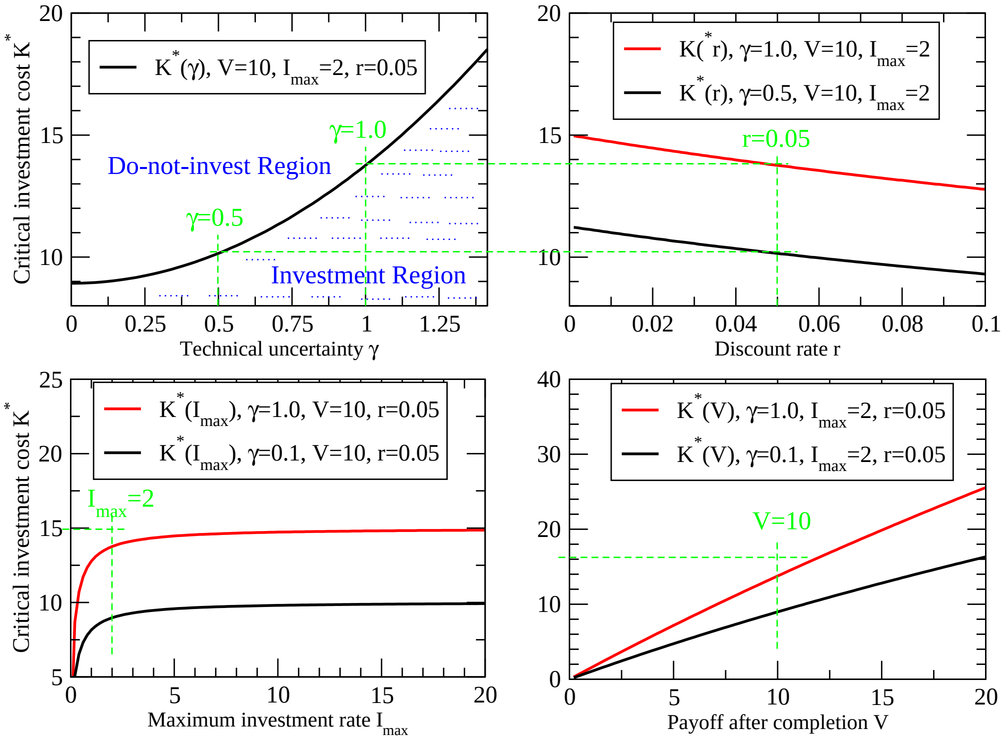


Figure 3.5.: Comparative statistics of the basic model with technical uncertainty.

investment rate of $I_{\max} = 2$ cause critical cost to completion to be less than $K^* = 8.93$ in a world of certainty (see Eq. (3.8)). This value is the starting point of the upper left graph showing the dependence of K^* on γ. The line ascends steeply illustrating how important it is to consider technical uncertainty, especially for R&D projects where γ can be large. This is also confirmed in the other graphs where the functional relation of K^* to the parameters is always shown for two levels of γ. Note that in an R&D project, γ can easily reach values of 0.5 to 1.0.[20] In comparison, $\gamma = 0.1$ is close to the certainty case. The dependence of K^* on r appears in the upper right part of Fig. 3.5. An increase in r lowers the critical cost to completion. r affects the value of the project as it is seen today.[21] As can be inferred from the lower right figure, a decrease in V reduces the region of investment as K^* decreases. Obviously, if the project does not yield any payoff, investment is never optimal. The lower left graph shows the dependence of K^* on $I_{\max}$. If the firm can invest more at a time, the region where investment is profitable is enlarged. Indeed, K^* depends more sensitively on $I_{\max}$ the smaller it is (in our numerical example, if $I_{\max} < 2$). This means the firm intends to reduce cost

[20] E.g. we estimate uncertainty in offshore wind park investment to be around 0.5. See Section 3.4.

[21] For $r = 0$, an analytical expression for the solution of Eq. (3.7) can be found. It has the form $F(K) = V - K + f(K, V, \gamma)$. This splits the value of investing into the value of a project that can not be abandoned (first term) and the value of the abandoning option (second term). See Dixit and Pindyck (1994), p. 349.

	$\gamma = 0.0$	$\gamma = 0.5$	
K	$F(K)$	$F(K)$	Paths stopped
5	4.1	4.2	14 of 10000
6	3.0	3.1	45 of 10000
7	2.0	2.1	145 of 10000
8	0.9	1.3	559 of 10000
9	0.0	0.6	2049 of 10000
10	0.0	0.1	7124 of 10000

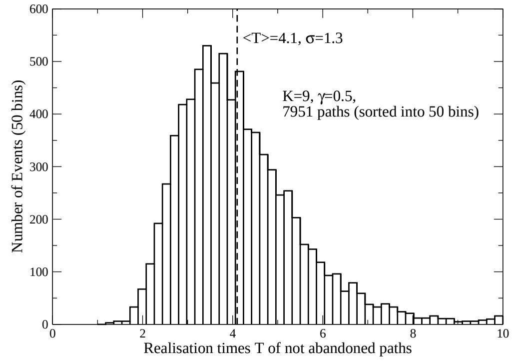


Figure 3.6.: Values of the investment opportunity $F(K)$ for technical uncertainty $\gamma = 0.0$ and $\gamma = 0.5$. The histogram to the right shows the distribution of completion times of paths not abandoned.

and to resolve uncertainty as fast as possible by preferring a short project time. Thus, in particular for long-term R&D projects, it is beneficial if investment resources can be expanded. However, there is a limit for the optimal investment approached from below and given by the expected cash-flows from the project. Uncertainty boosts this value from $K^* = 10$ (case of certainty) to almost $K^* = 15$.

Tab. 3.6 compares the value function $F(K)$ without and with uncertainty for different values of K. For $K = 9$, the deterministic critical threshold for investing is reached. But $F(K) = 0.6$ if $\gamma = 0.5$. Hence, investment is still profitable. This difference is measured by how much the investment opportunity is underestimated if uncertainty and irreversibility are neglected. To compare the magnitude, note that $F_{\text{max}} = 7.8$. This maximum is attained in the case that the project comes at no cost. Furthermore, given $K = 9$ and $\gamma = 0.5$, the option to abandon will be exercised for about 20 % of the 10000 paths. The graph to the right shows the distribution of finalisation times for the 7951 paths that are not abandoned. From this histogram, we can deduce a mean completion time of $< T >= 4.1$ and a standard deviation of $\sigma = 1.3$. Remarkably, there are 14 events in the bin for $T = 10$. If only abandoned paths are sorted, there are 100 events in that bin. The mean completion time and the standard deviation for abandoned paths are larger, i.e. $< T >= 5.7$ and $\sigma = 1.8$. For 59% of the abandoned paths, investments are stopped within the first quarter of the mean completion time, i.e. within $< T > /4 = 1.025$. The mean time of abandoning is slightly smaller with $< T >= 1.2$ and standard deviation $\sigma = 1.1$.[22] The number of abandoned paths grows approximately according to $0.02 * \exp(1.26 * K)$.

3.3.4. Limitations and conclusions

The basic model of sequential investment decisions under technical uncertainty neglects the origin of financing for the capital investment. Thus, it is either assumed that the

[22] The histogram for these numbers is given in Fig. A.1.

investment decision can be separated from the decision of its financing (Modigliani and Miller, 1958) or that the firm is able to completely self-finance the project. However, at least for smaller enterprises as well as new start-ups, in-house resources are likely to be limited. Moreover, capital markets are imperfect due to transaction costs or information asymmetries between the financier and the investor or other agents.[23] This can lead to higher costs for external financing and the rationing of credits, see e.g. Greenwald et al. (1984) and Hall (2002). Findings in the literature are somewhat mixed. First, results depend on the framework of study (static or dynamic set-up). Second, they depend on which option value dominates the model (the value of postponing the investment or the value of accelerating investments). Extending the model of McDonald and Siegel (1986) by allowing for a firm to simultaneously determine its investments and capital structure, Mauer and Triantis (1994) find that "... if a levered firm uses the investment and operating policies of an equivalent unlevered firm, there is a negligible loss in firm value". In the dynamic framework the firm has an option to delay the investment. This makes shields, e.g. from tax-advantaged depth financing, less effective. Other findings from the real options literature show that financing constraints can decrease the value of waiting as well as the critical threshold for investing (Boyle and Guthrie, 2003). This leads to suboptimal investment rushes[24] since the firm tries to avoid future financing risks. McGee (2010) develops a model that includes two constraints: the first due to the irreversibility of capital investments and the second a financing constraint. He finds that only for the fastest-growing firms does the investment rush due to financing constraints dominate the value of waiting. This is a result of irreversibility and certain types of uncertainty (e.g. market correlated input cost).

However, these findings apply to capital investments in general. Hall (2002) reviews theoretical and empirical evidence of the impact of financing constraints on R&D investments. He summarises that "...The evidence for a financing gap for large and established R&D firms is harder to establish. It is certainly the case that these firms prefer to use internally generated funds for financing investment."[25] On the other hand, the theoretical contributions discussed in Hall (2002) are not based on dynamic or real options analysis. As we can see, the basic model of Pindyck (1993) can provide insights into R&D investment decisions of established firms, firms which can rely on different sources of internal financing and thus hedge financing risks.

The study of financing constraints for newly founded, small-, and medium-size enterprises is left to future research. A possibility to include this feature would be to model the availability of credits in dependence of stochastic shocks. Another question arises

[23] For example, there are also information asymmetries between researchers and managers of an R&D project, making moral hazard a potential.

[24] In a dynamic model with stochastic financing constraints, Kasahara (2008) obtains that it is necessary to take future risks into account, and that this can induce a more active investment behaviour. In his model, the firm completely relies on internal funding and can only invest if the capital stock equates at least to the maximum productive investment rate.

[25] Yet, Hall (2002) notes that he ignores "arguments based on R&D spillovers and externalities. There is a good reason to believe that the latter are a much more important consideration for large established firms, especially if we wish those firms to undertake basic research that is close to industry but with unknown applications."

from the fact that for R&D investments technical uncertainty is more relevant than input cost uncertainty (Kort, 1998; Czarnitzki and Toole, 2008). For this reason we did not incorporate this type of uncertainty (second limitation). Because, with technical uncertainty there is no incentive to postpone decisions as new information only arrives when the firm is active and invests, it would be interesting to study the relationship between technical uncertainty and imperfect capital markets since technical uncertainty leads to a value of investing. This could be done by firstly, letting the maximum productive investment rate $I_{\max}$ develop stochastically. Secondly, a minimal investment rate $I_{\min}$ could be introduced reflecting that e.g. payments for researchers need to be continued. The model could then be solved by Monte Carlo simulation using the following investment rules: 1) in the region of investment and in the case that the firm faces no financing constraints, investment at $I_{\max}$ is chosen, 2) if financing is constrained, but it is still profitable to invest, the firm invests with $I_{\max} \geq I \geq I_{\min}$, otherwise 3) the firm refrains from investments.

A third limitation in our model is that competition and the impact of rivals are not considered. Competition can lead to an innovation race in order to realise a first mover-advantage that is rewarded with market power. This calls for a game-theoretic analysis. There are other exogenous factors that can influence the development of the remaining cost to complete an R&D project, for example, knowledge spillovers. Kort (1998) extends his model of a single firm replacing Eq. (3.5) by

$$dK(t) = -I(t)\exp(\omega t)dt \ . \tag{3.17}$$

The constant parameter $\omega > 0$ denotes the rate of technological development outside of the firm. Note that the model becomes deterministic. Kort (1998) obtains that this modification generates a value of waiting in that the firm now has an incentive to await technological progress and postpone investments.

A fourth limitation is that the payoff from R&D investments is assumed to be certain and, furthermore, not subject to decreasing returns. Schwartz (2004) studies the effect of stochastic cash-flows C from the project. He introduces a post-patent cash-flow as being a multiple of the cash-flow ($M \times C$). Both determine the value of the project V. Model equations are specified in the following way

$$\begin{aligned} dC &= \alpha\, C dt + \phi\, C\, d\omega \ , \\ V(C,T) &= M \times C \ . \end{aligned} \tag{3.18}$$

Thus, the net cash-flow rate is model-led as a geometric Brownian motion. Increments dw are correlated with the market portfolio and with the expected cost for completing the project. Drift parameter α describes characteristics of a particular R&D programme. M is a measure of competitiveness and it reaches zero when the market becomes perfectly competitive. By running a Monte Carlo simulation, Schwartz (2004) yields the result that the project value and the probability of abandoning the project increase when the cash-flow rate as well as the terminal cash-flow multiple M increase.

Finally, we have neglected costs to shut down the R&D project. However, this is justifiable as the majority of R&D costs are wages and salaries of highly specialised engineers and scientists (Hall, 2002). Moreover, installations and equipment are likely to be re-used and thus might not cause large sunk costs.

Despite these limitations, the basic model allows us to elucidate the dynamics of investment decisions of a firm endowed with sufficient resources to self-finance an R&D project. Generic features of R&D investments can be incorporated. In the following sections of this chapter, Pindyck's (1993) basic sequential decision model is extended to study a firm's R&D investment decisions in different environmental/technology policy frameworks. One model explores offshore wind park investment under feed-in tariffs. The second model analyses policy incentives to spur R&D for energy-saving technologies. In addition to technical uncertainty, policy uncertainty is introduced in Chapter 5 to study the relationship between these two types of uncertainties.

3.4. An application to offshore wind farm investment

3.4.1. Motivation: Rostock's offshore wind park Baltic 1

By 2020, 20% of EU energy is targeted to originate from renewable sources (KOM, 2006). The German Renewable Energy Sources Act of 2009 sets an even more ambitious goal of 30% for the share of renewables in total electricity consumption by 2020. A huge potential is seen for offshore wind energy amounting to a long-term goal of up to 25 GW of cumulative capacity for Germany by 2030 (BMU, 2007). Currently, the capacity of offshore wind parks in operation is only 42 MW. That leaves Germany behind Great Britain (2.4 GW), Sweden (2.2 GW), Denmark (2.2 GW), Netherlands (1.2 GW), and Belgium (300 MW). However, nearly a capacity of 10 GW (approx. 25 parks) has already been licensed and meanwhile a capacity of 17 GW (approx. 28 parks) is currently undergoing the approval process (DENA, 2010; EWEA, 2009).

Since 1991, when the first park was installed near Vindeby in Denmark, offshore wind technology developed into a cutting-edge technology. Naturally, a large amount of uncertainty is involved when planning, installing, and operating such a farm. This includes, foremost, technical cost uncertainty but also uncertainties related to the cost of input and/or output factors. Technical cost uncertainty exists due to the still limited experience with offshore wind technology. Therefore, a substantial amount of R&D costs need to be considered, e.g. for finding the optimal location, anchoring the foundation in the sea, establishing a grid connection, or maintaining the farm under sea weather conditions. Input cost or output cost uncertainties, on the other hand, can also be correlated with the economy. For example, turbine costs are likely to fluctuate with changes in the world wide demand for steel and other metals. Output cost can e.g. be subject to changes in policies as wind farm operators rely on guarantees to sell electricity to the market. The yearly wind yield can only be estimated as it is very demanding to forecast wind and weather conditions. Therefore, electricity cannot be produced constantly, leading to typical load factors of 35 % of the installed capacity (ODE, 2007).

Consequently, the decision to invest in an offshore wind farm is risky and moreover involves a high amount of irreversible cost since investments are site-specific and hence only partially recoverable. The real options approach is a way to evaluate the opportunity to invest under these circumstances. Among others, Pindyck (1993) applies a real options model to evaluate nuclear power plant investments under technical and cost uncertainty. Kjaerland (2007) derive a real option value of hydro-power investments in a non-sequential model under uncertainty of returns. Davis and Owens (2003) evaluate US onshore wind power investments under energy price uncertainty.

We will apply real options theory to review the investment decision for the planned offshore farm 'Baltic 1' currently being built near Rostock. This is a particularly interesting project as it is expected to run as Germany's first commercial offshore wind farm. We will use a sequential investment model reflecting that the project needs time to be realised. At any time, the project can be stopped if the investment costs exceed expected payoffs. Technical uncertainty is explicitly included in the model. The basic model that we will extend was developed by Pindyck (1993). We will compare two policy regimes that are currently active in Germany. The first one offers a sprinter bonus for offshore wind farms if they are in operation before 2016. This higher electricity feed-in tariff is replaced by a baseline tariff after 12 years. The second policy regime considers only the baseline tariff. Costs for operation and maintenance as well as the expected life time of the wind park affect the expected payoff. Therefore, we will take account of different schemes.

In the next section, we will extend the sequential investment model introduced in the beginning of this chapter to the policy framework relevant to offshore wind farm investments. This is followed by an analysis of available data of European offshore wind parks in order to specify necessary model parameters. Finally, we discuss results and draw conclusions for this application.

3.4.2. The model with an extension for feed-in tariffs

A large energy corporation plans to self-finance and build an offshore wind farm. We assume a maximum productive investment rate as the realisation of the investment project involves a considerable amount of R&D costs and takes time, e.g. for planning, getting a license, constructing, and testing the farm. Thus, the firm has to solve a sequential investment problem when assessing the opportunity to implement the project. At any point in time it may turn out that the continuation of the investment is not profitable. But the firm has the option to abandon the project. Though, the project is stopped, the invested money cannot be recovered. This makes the investment irreversible. Furthermore, the project can only be realised if all investment stages have been passed successfully. Thus, the firm holds a sequential call option.

We assume that the main source of uncertainty is the scientific/technical difficulty in carrying out the offshore wind farm project. This is realistic as salaries for specialists and engineers sum up to 40 % of installment and decommissioning costs (e.g. ODE (2007)). Even if input prices were known for sure and all plans that depend on factors outside of the firm's influence would turn out perfectly, positive or negative changes could occur. Thus, the firm does not know how installation costs will develop and how long it will take to put the farm into operation. Actual costs are only known for certain once the project is finalised. This type of uncertainty is site-specific and typical for a project using cutting-edge technologies - it can only be resolved when investment is actually undertaken. Otherwise, learning to deal with the difficulties stops. Therefore, facing technical uncertainty, there is no incentive to postpone the project.

In comparison to uncertainty about the technical progress, the firm shall be, at least relatively, certain about the outcome of the investment. This can be justified as wind offshore technology is a capital-intensive technology. Investments for establishing the farm make up to 80% of the cost expected during the total lifetime of the plant (Blanco, 2009). Moreover, the policy framework of feed-in tariffs is fixed by law supporting a relatively certain prediction of future cash-flows. Finally, we assume that the firm completely self-finances the project.

Despite uncertainty, the firm is able to form an expectation about the remaining cost to completion $K(t)$ such that $K(t) = \mathcal{E}(\tilde{K}(t))$ with $\tilde{K}$ being the actual total cost and $\mathcal{E}$ being the expectation value operator. The project is completed when $K(T) = 0$. This defines the time T at which the wind farm is operable. With $I(t)$ being the investment rate at time t, γ denoting technical uncertainty, and $dw(t)$ denoting the increments of a Wiener process, the evolution of the expected cost to completion is modelled as in Pindyck (1993)

$$dK(t) = -I(t)dt + \gamma\sqrt{I(t)K(t)}\, dw(t) \ . \tag{3.19}$$

The decision whether to invest or not is straightforward. The firm invests if the expected payoff from the wind park is higher than the sum of investments made. In order to get the highest possible net payoff, the firm can control the flow of investments at each instant in time. This can be formalised in a value function $F(K(t))$ for the investment opportunity

$$F(K(t)) = \max_{I(t)} \mathcal{E}_0 \left[\int_T^{\infty} P \exp(-rt)dt - \int_0^{T} I(t) \exp(-rt)dt \right] \ . \tag{3.20}$$

The first term describes the discounted cash-flows after the plant is installed. P is the constant cash-flow per period and r is the discount rate. In sum, the firm will hold an asset worth $V = P/r$. The second term is the total expenditure needed to realise the project. If investment is optimal, $F(K(t))$ satisfies the following inequality[26]

$$-1 - \frac{\partial F(K(t))}{\partial K(t)} + 0.5\,\gamma^2\, K(t) \frac{\partial^2 F(K(t))}{\partial K(t)^2} > 0 \ . \tag{3.21}$$

Equality in (3.21) defines a critical value of expected investments required to complete the project K^*. At this critical threshold, the value function $F(K^*)$ becomes zero. If the expected cost to completion are smaller than K^*, the firm will invest the maximum. Otherwise the firm will not invest. The optimal investment rule is

$$I = \begin{cases} I_{\max} \ , & \text{if} \quad K < K^* \ , \\ 0 \ , & \text{if} \quad K > K^* \ . \end{cases} \tag{3.22}$$

[26] This equation satisfies Eqs. (3.12, 3.13). It is not a stochastic differential equation anymore.

As a result, it is sufficient to calculate K^* which can be done numerically. The critical value is a free boundary between the region of investment and the region of non-investment, which fulfills the conditions

$$F(0) = V = P/r \ , \quad \lim_{K\to\infty} F(K) = 0 \ , \quad F(K^*) = 0 \ , \quad F'(K^*) = 0 \ . \tag{3.23}$$

The first condition describes the discounted payoff V after completing the R&D project. The second condition states that for a large K it is not reasonable to start the project at all. The two last boundary conditions are matching conditions between the regions of investment and non-investment.

Next, we extend the model to describe the current policy framework. The German Renewable Energies Resources Act from 2009 (BMU, 2009) supports offshore wind energy with guaranteed feed-in tariffs for wind generated electricity. The act also sets an obligation for regional or national grid utilities to purchase the offered electricity. The guaranteed selling price for electricity is 0.035 EUR/kWh. In addition, a sprinter bonus is offered for offshore wind parks if they are in operation before January 2016, amounting to 0.15 EUR/kWh during the first 12 years. Taking this and the limited lifetime of the plant into account, we need to modify the first term of Eq. (3.20) as P is now time dependent. We obtain

$$\int\limits_{T}^{T+T_1} P_1\, \mathrm{e}^{-rt}\, dt + \int\limits_{T+T_1}^{T+T_1+T_2} P_2\, \mathrm{e}^{-rt}\, dt + \int\limits_{T+T_1+T_2}^{\infty} P_3\, \mathrm{e}^{-rt}\, dt = \int\limits_{T}^{\infty} \tilde{P}(t)\, \mathrm{e}^{-rt}\, dt \ . \tag{3.24}$$

T is the completion time of the project. For a time T_1, the sprinter bonus is used to calculate the firm's payoff. In the case considered, the lifetime of the plant ends after another period of T_2. The left-hand side of Eq. (3.24) can be split into terms, which depend on the stochastic completion time T and those that do not. This allows us to integrate the three integrals into one (right-hand side). Therefore, apart from Eq. (3.20), only the first of the four boundary conditions in Eq. (3.23) is affected by our extension for the policy regime. We need to replace P with $\tilde{P}$ given by

$$\tilde{P} = P_1 + (P_2 - P_1)\mathrm{e}^{-rT_1} + (P_3 - P_2)\mathrm{e}^{-r(T_1+T_2)} \ . \tag{3.25}$$

In the following application of the sequential investment model, we will consider four different policy/lifetime scenarios:

1. **Sprinter bonus, 20 years running time**: During the first 12 years, electricity can be sold at the bonus price of 0.15 EUR/kWh. From year 12-20 the baseline feed-in tariff of 0.035 EUR/kWh is guaranteed. The wind farm is expected to run 20 years (Vattenfall, 2010). Thus, $T_1 = 12$, $T_2 = 8$, and $P_3 = 0$.

2. **Sprinter bonus, infinite running time**: For the first 12 years, a price of 0.15 EUR/kWh is guaranteed. Afterwards, the payoff will be calculated with the baseline feed-in tariff of 0.035 EUR/kWh. The farm operates forever ($P_2 = P_3$).

3. **Baseline feed-in tariff, 20 years running time**: Electricity can only be sold at the baseline feed-in tariff of 0.035 EUR/kWh (no sprinter bonus). The farm is expected to run 20 years. Thus, $P_1 = P_3 = 0$ and T_1=0, $T_2 = 20$.

4. **Baseline feed-in tariff, infinite running time**: The baseline feed-in tariff of 0.035 EUR/kWh is guaranteed forever and the lifetime of the farm is not limited. Thus, $P_1 = 0$, $P_2 = P_3$, $T_1 = 0$.

3.4.3. Data sources and parameter derivation

Preparations for the construction of the offshore wind park Baltic 1 began in July 2009. It is planned to go into operation at the end of 2010 making Baltic 1 the first commercial wind park in Germany. Other German wind parks, e.g. Alpha Ventus, are so far only running as test fields. Baltic 1 will an installation of 21 wind turbines near Rostock, 15-16 km north of the peninsula Darss/Zingst. With a final installed capacity amounting to 48.3 MW, it will serve about 50.000 households for at least 20 years. The data are summarised in Tab. 3.1.

In order to calculate the option value of investment for Baltic 1, we need estimates for the uncertainty parameter γ, expected initial investment cost $K(0)$, the maximum rate of investment $I_{\max}$, and the net value of the wind farm's capacity P. The net value of capacity is given by expected payoffs less expected cost for operation and maintenance (short: O&M costs). The latter range from 0.017 - 0.045 EUR/kWh (KPMG, 2007)[27] and also include reserves for deconstructing the wind farm. Expected investment cost will be estimated in the next section by a multiple regression analysis of offshore wind farm data. For simplicity, the maximum rate of investment will be assumed constant over the years of construction.

Location:	Baltic Sea, North of Peninsula Darss/Zingst
Distance from shore:	16 km
Size:	approx. 7 km^2
Depth:	16-19 m
Total capacity:	48.3 MW
Annual yield:	176.4 GWh/a
Average wind speed:	9 m/s
Number of turbines:	21, each 2.3 MW
Number of transformer stations:	1
Expected running time:	at least 20 years
Expected building time:	2 years, 6 years incl. planning and testing

Table 3.1.: Data for Offshore wind park Baltic 1 (Source: Vattenfall (2010)).

[27] O&M costs are thus 3.06-8.10 MEUR/year for operating Baltic 1. We take the lower number for the low and the upper number for the high O&M regime.

The expected construction period ranges between 1.5 and 6 years. Therefore, we will calculate values for 1.5 years, 2, 3, 4, 5, and 6 years. The maximum rate of investment is then simply given by dividing expected investment cost by the expected time of construction. However, this does not imply that the firm knows how much time is needed to build the farm. The derivation of expected investment cost and the uncertainty parameter γ follow.

Expected investment costs of Baltic 1

Data of 40 offshore wind parks are available from different sources (DENA, 2010; EWEA, 2009; KPMG, 2007; Snyder and Kaiser, 2009a,b). For 27 parks, investment costs (in US$) has been published in a single source adjusted for inflation (Snyder and Kaiser, 2009b). These are the most comparable investment cost data we could find. KPMG (2007) also analyse investment cost data using a data set of 27-30 wind farms. However, only average cost have been published in order to make data anonymous. Farms were grouped into three categories depending on their distance from the shore, water depth, and size of turbine. Using this categorisation, most data in Snyder and Kaiser (2009b) belong to categories 1 and 2. Planned German offshore parks, however, belong to category 3 due to their comparatively large distance from shore.

The average price of a MW capacity is about 1.85 ± 0.16 MEUR for the sample of Snyder and Kaiser (2009b). KPMG (2007) expects an average price of 2.2 MEUR per MW for planned but not realised farms in 2005. We will use data of Snyder and Kaiser (2009b) for further analysis although information on cost components is limited. In addition, we have compared data sources to check for comparability to other data. In case of differences, we have chosen the latest update available from EWEA (2009). Our final data set is attached in the appendix, Tab. A.2. The sample includes 27 wind farms. We calculated prices in EUR using the annual exchange rate for 2008 from the Statistical Data Warehouse of the European Central Bank with a EUR/US$ ratio of 1.4708.

Next, we run multiple regressions, including non-linearity tests, in order to find variables explaining expected investment costs. Candidates are the distance from shore, water depth, total capacity, age of farm, number, and size of turbines. For illustration, Fig. 3.7 shows the distribution of investment cost in Millions of Euro with dependence on possible explanatory variables. Investment costs are expected to grow with the distance from shore and water depth. Transport cost are likely to increase and special equipment and techniques could become necessary. For similar reasons, it is likely that investment cost would also grow with the capacity of the farm calculated from the number and size of turbines. If the number of turbines and their complexity increase, more material and sophisticated techniques are asked for.

We do not expect to see a significant time-dependence of investment cost in our sample covering a period of only 17 years. In the medium- and longterm however, costs due to technical difficulties in installing the farm will decrease with the growing experience in the offshore sector. Factor costs, on the contrary, are likely to continue to rise due to the growing world-wide demand for raw materials and metals.

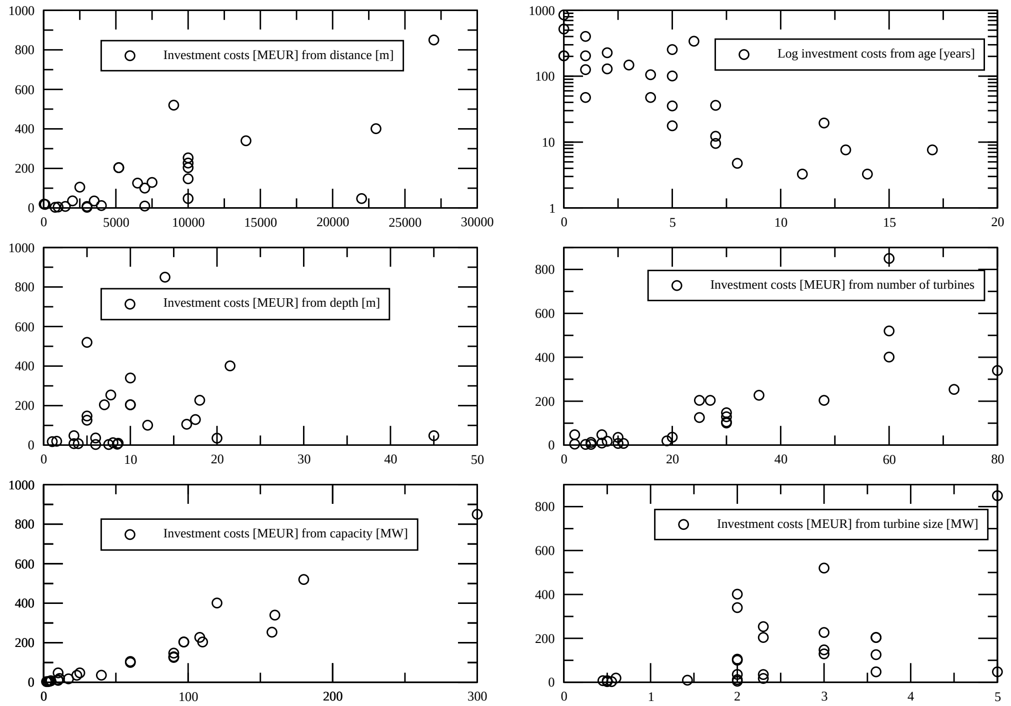


Figure 3.7.: Distribution of investment costs of offshore wind farms in Million Euro with regard to possible explanatory variables.

Dependent variable: Investment cost [MEUR]			
Explanatory variable	Model 1	Model 2	Model 3
Intercept	-45.074	-72.961	-37.658
Capacity in MW	2.308 (7.8 E-12)	2.376 (5.1 E-09)	2.224 (7.5 E-10)
Distance in m	0.005 (0.027)	0.006 (0.049)	0.006 (0.042)
Depth in m	–	-0.425 (0.812)	-1.202 (0.471)
Age in years	–	3.511 (0.263)	-
Observations	27	27	27
R-squared	0.936	0.941	0.937
adj. R-squared	0.931	0.930	0.929

Table 3.2.: Results of multiple regression to explain investment cost of offshore wind parks (confidence level: 0.95, P-Values in brackets).

Distance from shore	15 km	16 km
Investment cost [MEUR]	134.5	139.1
Investment cost per capacity [MEUR/MW]	2.785	2.879
Standard error [%]	38	37

Table 3.3.: Estimated investment cost for Baltic 1 in MEUR.

A check for collinearity showed that most variables are moderately correlated (< 0.6). However, the turbine size and the farm's age are strongly correlated ($= -0.86$) as are the number of turbines and the farm's capacity ($= 0.93$). Therefore, we will include only one from each pair of strongly correlated variables. Tab. 3.2 describes the three best regression models ranked according to their adjusted R-squared. We find that capacity and distance are a significant factor for investment costs of the sample. Both, as expected, increase investment costs when growing. Snyder and Kaiser (2009b), running multiple regressions, and KPMG (2007), running simple regressions, also find that the depth is significant in explaining investment cost. However, they estimate that this influence is comparatively small.

Next, we calculate expected investment cost for the offshore wind park Baltic 1 using the best regression model, Model 1, and data given in Tab. 3.1. We obtain an expected investment cost of 139 MEUR $\pm$ 37% for a distance of 16 km and 135 MEUR $\pm$ 38% for a distance of 15 km (see Tab. 3.3). We take these as the lower and upper boundaries for further analysis.

Estimates of uncertainty parameters

Technical uncertainty is site-specific and time-independent, whereas cost uncertainty grows with the time horizon. Both types of uncertainties can be decomposed and extracted by analysing time series and cross-sectional variations of these data (see e.g. Griffiths and Anderson (1989); Heshmati and Kumbhakar (1994); Pindyck (1993)).

Technical uncertainty follows from the standard variance of expected investment cost assuming the sample is filtered for its time dependency. The variance of expected investment cost is given by Eq. (3.3). We did not find a significant dependency of investment cost on the year of construction or the farm's age in the data. Thus, depending on the assumed distances from shore, we have

$$\gamma = \begin{cases} 0.489\ , & \text{for} \quad 15\,\text{km} \quad , \\ 0.503\ , & \text{for} \quad 16\,\text{km} \quad . \end{cases}$$

Input cost uncertainty can principally be estimated from the trend of time series. However, available data cannot be used for this, because first, they only sparsely cover a period of 17 years, and second, the data do not show a significant dependence on the farm's age, neither linear nor in higher orders. This was also found by Snyder and Kaiser (2009a). Apart from the limitations of the data, opposing trends affecting investment costs could be another reason. On the one hand, the sector-wide learning rate and economies of scale are causing a downward trend for investment costs. On the other hand, costs for steel and copper have been rapidly growing since 2002. The demand for wind turbines is higher (and is predicted to remain higher) than the supply, which in turn affects market prices and delivery times, see Blanco (2009); ODE (2007); Ernst&Young (2009); Snyder and Kaiser (2009b). In total, it is not clear which effect will dominate in what years. Only long-term forecasts for the year 2030 and beyond predict a decline in cost prices (Ernst&Young, 2009; ODE, 2007).

However, for our analysis of Baltic 1, we expect technical uncertainty to be more relevant than input cost uncertainty for two main reasons. First, wind offshore technique is a very new technology and the establishment of each farm can be seen as a fresh experiment. KPMG (2007) point out that geographic conditions, particularly in Germany, lead to higher project risks as farms are planned to be installed comparatively far away from the shore. Second, the building time of 1.5-6 years is rather short making it less likely for input cost prices to influence the project. It is realistic that they are covered in contracts set up 2-3 years in advance. Hence, we will only study the influence of technical uncertainty on expected investment cost and on its critical threshold.

3.4.4. Results from the real option model

Conventional net profit value of Baltic 1

We start our analysis by neglecting uncertainty. We calculate net profit values resulting from yearly cash-flows in the different policy regimes. Net profit values depend on construction times and the costs for operation and maintenance of the farm. We assume a risk-adjusted discount rate of $r = 5\%$.

Our results for the value function $F(K(t))$ and the critical threshold of investment costs K^* in the case of certainty are given in Tab. A.3 in the appendix. In principle, it is worth investing in Baltic 1 if $F(K)$ is positive. In this case, expected payoffs from operating the offshore farm exceed the expected cost to completion. K^* separates the regions of investment and non-investment. Only if expected cost K are below K^* is investment profitable. Neglecting uncertainty, we find that it is profitable to invest in Baltic 1 if a sprinter bonus for offshore farms is guaranteed and if the construction time is less than 4 years. This is independent of the amount of O&M costs. The finding also holds for both distances of the park from the shore, 15 km and 16 km. However, if the construction takes longer than 4 years, the investment is only profitable if costs for O&M are low. For the expected construction time of 1.5 years, we find that critical investment cost are 214.4 MEUR/ 157.0 MEUR (low/ high O&M costs) and 214.8 MEUR/ 157.2 MEUR (low/ high O& M costs) for a distance of 15 km and 16 km from shore, respectively. The slightly larger values for the longer distance is a result of the higher maximum productive investment rate at 16 km. Thus, the total remaining expenditure required to install the farm can be reduced faster.

The result also depends on the discount rate. However, in a conventional feasibility study for offshore wind farms in the Apulia region of Italy, Pantaleo et al. (2005) also

		$\gamma = 0$		$\gamma \approx 0.5$	
		15 km	16 km	15 km	16 km
high O&M	K^*	157.0	157.2	177.6	176.7
	F(K)	22.6	18.2	24.9	20.8
low O&M	K^*	214.4	214.8	243.0	241.8
	F(K)	81.7	77.3	82.6	78.2

Table 3.4.: Value of investment $F(K)$ and critical investment cost K^* for Baltic 1.

use a discount rate of 5%. Jeske and Hirschhausen (2005) take a risk-adjusted discount rate of 4% in their sensitivity analysis for two planned German offshore parks carried out for the policy framework of 2004. However, if we lower the discount rate by 1%, critical investment cost only slightly increase, e.g. from 157.2 MEUR to 158.5 MEUR in case of 1.5 years construction time, 20 years of operation time, sprinter bonus, high O&M costs, and a distance of 16 km. As results are comparatively insensitive to changes in the discount rate, we keep the discount rate at 5%.

Including technical uncertainty

When technical uncertainty is present, the value function $F(K(t))$ as well as the critical investment cost to completion K^* increase. Thus, we can confirm an incentive to invest if irreversibility and the option to abandon are taken into account. Tab. 3.4 summarises the results for an expected construction time of 1.5 years (which is the current plan), an operation time of 20 years, and a guaranteed sprinter bonus. Extended results for $F(K)$ and K^* with varying policies, technical uncertainties, investment costs, construction times, operation times, and costs for O&M are available in Tabs. A.4 and A.5. In order to get an understanding of the importance of technical uncertainty, we compare the values under the current policy regime at an expected construction time of 1.5 years. In this case, technical uncertainty raises K^* by as much as 12 %. Even with a construction time of over 3 years, the investment is still profitable regardless of the distance from shore (15 km/ 16 km) or the corridor of costs for operation and maintenance.

We can furthermore confirm that sprinter bonus guarantee is crucial. If only a baseline tariff is offered, $F(K)$ is zero and hence, offshore wind projects comparable to Baltic 1 are not profitable. This is caused by high investment costs as well as high costs for operation and maintenance. The reduction of these costs, e.g. by learning or economies of scale, will be a major task if wind generated energy shall become competitive. Assuming a sprinter bonus and an operation time of 20 years, Tabs. A.6 and A.7 moreover show the sensitivity of K^* to the maximum productive rate of investment (or expected time of construction). The standard variation of the samples with low/high O&M and 15/16 km is smaller than 6 %. In numbers, uncertainty raises mean critical cost to completion with low/high O&M from K^*=199.7 MEUR/ 148.7 MEUR ($\gamma = 0$) to K^*=227.8 MEUR/ 169.1 MEUR ($\gamma \approx 0.5$) in case of 15 km and from K^*=200.4 MEUR/ 149.1 MEUR

T [years]	O&M	V [MEUR]	stopped paths	$< T >$ (σ)	t_a
1.5	high	164	458 of 10000	1.46 (1.5)	371 of 458
1.5	low	228	30 of 10000	1.50 (0.6)	9 of 30
2.0	high	164	505 of 10000	1.94 (0.7)	366 of 505
2.0	low	228	33 of 10000	2.00 (0.7)	6 of 33
3.0	high	164	596 of 10000	2.90 (1.0)	356 of 596
3.0	low	228	43 of 10000	2.99 (1.1)	2 of 43
4.0	high	164	713 of 10000	3.84 (1.3)	364 of 713
4.0	low	228	43 of 10000	4.00 (1.4)	1 of 43
5.0	high	164	832 of 10000	4.78 (1.6)	378 of 832
5.0	low	228	16 of 10000	4.96 (1.7)	1 of 16

Table 3.5.: Risk of non-profitable investment in Baltic 1.

($\gamma = 0$) to K^*=227.0 MEUR/ 168.4 MEUR ($\gamma \approx 0.5$) in case of 16 km.

In addition to solving the sequential decision model by dynamic programming, we run a Monte Carlo simulation with 10000 paths. The total simulation time is 10 years and the number of time steps is 30000. Other parameters are the same as in the numeric model.

The average completion time $< T >$ for the installation of the wind farm ranges between 1.46 ± 0.5 and 4.96 ± 1.7 years depending on the expected construction time T and the O&M regime, see Tab. 3.5.[28] We obtain that 5-9 % (in case of high O&M costs) and up to 0.4 % (low O&M costs) of the 10000 paths are abandoned under the current policy framework.[29] For 45-81 % of these abandoned paths in the high O&M regime (for varying expected construction times T), investments are stopped within the first year. As expected, the data show that the option to stop the project is more often exercised as the expected completion time increases. In the case of low O&M costs, only 16-43 paths out of 10000 are abandoned. As these numbers are low, we cannot draw a statistical conclusion on the likely time of stopping investments.

3.4.5. Limitations and conclusions

In coming years, offshore wind farms will contribute largely to the generation of energy. However, experience with offshore technology is still limited. Thus, these projects are very risky. Baltic 1 with a planned capacity of 48.3 MW is currently under construction and will run as the first commercial offshore wind park in Germany. We have estimated the value for investment in a real options approach taking into account technical uncertainty. This type of uncertainty is a major source of uncertainty for capital and R&D

[28]In Tab. 3.5: T is the expected construction time, V is the expected payoff, $< T >$ is the average completion time, σ is the corresponding standard deviation, and t_a gives the number of paths abandoned within the first year of implementation.

[29]Results are given for a distance of 15 km from shore. Results for 16 km do not differ substantially.

intensive technologies. Uncertainty related to cash-flows from the project are incorporated via upper and lower boundaries for expected operation and maintenance costs. Environmental policy takes the form of two types of feed-in tariffs (baseline tariff and sprinter bonus).

We performed multiple regressions and found expected costs to sum up to 134.5/ 139.1 MEUR depending on the distance from shore. Technical uncertainty for Baltic 1 was estimated to be of the magnitude $\gamma = 0.5$ allowing critical investment costs to rise by 12 %. Results furthermore show that under the German Renewable Energy Resources Act of 2009 wind farms comparable to Baltic 1 can be run profitably, but policy support, by guaranteeing a sprinter bonus tariff, is crucial. In this case, the risk for investing in a non-profitable project is not higher than 9 %. We did not find evidence for input cost uncertainties in the data. However, it is expected that they will play a major role in the future. Technical uncertainty should instead decrease with growing experiences establishing and running offshore wind farms.

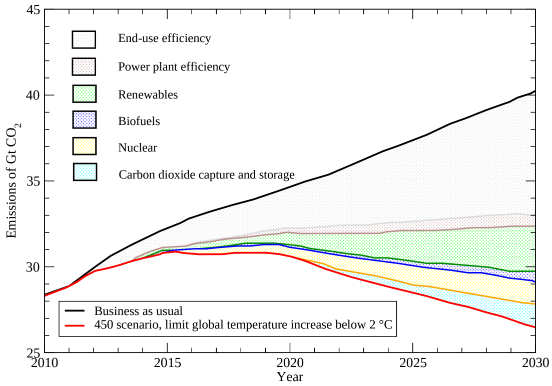
Limitations of the model lie in our neglect of financing issues, rivalry, and possible costs for abandoning. Then again, as discussed in Section 3.3.4, the theoretical and empirical evidence suggests that established firms are less likely to face R&D financing gaps (see also Mauer and Triantis (1994); Kort (1998); Hall (2002); Czarnitzki and Toole (2008)). Competitors are likely to spur a firm's investments in order to gain advantage and expand market power, thereby potentially increasing critical investment cost. The inclusion of midstream deconstruction cost would have the following impacts. On the one hand, additional costs would drive K closer to K^*, while on the other hand, they would generate opportunity costs for stopping the project raising the incentives to continue with investments. Moreover, results are not very sensitive to changes in the maximum productive investment rate. Thus, we expect the total effect to be small[30]. To improve the realism of the model, separate project stages could be included that are connected with specific risks and have to be passed successfully. Finally, only limited data of offshore parks and costs, as well as their breakdown, are available to date. Despite the limitations, the application provides an understanding of the magnitudes of parameters and their impacts. These estimates are useful in further theoretical analysis increasing the realism of parameter values.

3.5. An application to environmental R&D decisions

3.5.1. Motivation: energy efficiency to mitigate climate change

Any decision to invest in R&D is a decision under uncertainty as future conditions, e.g. future costs and benefits, market conditions etc., are not known beforehand. This is an important question of how policy measures can provide incentives to spur R&D. As the

[30] Note that wind park operators are required to give a loan guarantee for decommissioning. However, due to a lack of experiences actual cost are not known. ODE (2007) estimate decommissioning cost per turbine of about 0.4 MEUR (2006 prices). This implies about 8 MEUR for Baltic 1. The most pessimistic estimate we found sums up to 13 % of installed costs (Bayou, 1997). These costs can serve as an upper estimate for (sequential) midstream deconstruction costs.



	Abatement 2020	Abatement 2030	Investment 2010 -2020	Investment 2021 -2030
Efficiency	2517	7880	1999	5586
- End-use	2284	7145	1933	5551
- Power pl.	233	735	66	35
Renewables	680	2741	527	2260
Biofuels	57	429	27	378
Nuclear	493	1380	125	491
CCS	102	1410	56	646

Figure 3.8.: Abatement potential of and necessary investments in Billion of USD in different energy sources or efficiency measures to limit global temperature rise to below 2 °Celsius. Source: IEA (2009).

world is facing the threat of climate change, policy measures supporting the development of energy-saving technologies, and thereby increasing the potential for emissions reductions, are of particular interest.

In a recent scenario approach by the International Energy Agency in its World Energy Outlook 2009, IEA (2009), consequences and policy implications to limit an increase of the global temperature to below 2 °C were studied.[31] Two findings are especially relevant for the purpose of our analysis. First, energy efficiency plays a major role in mitigating climate change. Fig. 3.8 illustrates that energy efficiency measures have the potential to contribute almost two thirds of the necessary abatement of green house gases in 2020 and about 50 % in 2030.[32] Second, IEA (2009) states that additional investments of about 10.5 Trillion USD in energy infrastructure and energy-related capital stocks are required in comparison to the business-as-usual scenario. The latter would lead to a global temperature increase of about 6 °C. Thus, policy measures that can stimulate R&D investments are crucial in this respect.

This section analyses how R&D investment decisions in energy-efficient technologies are influenced by policy incentives when technical uncertainty is present. We will explore how environmental policy influences R&D efforts by the choice of an environmental instrument and by its intensity. In general, environmental policy has two impacts on the firm's decision. First, it will influence available investment resources. Second, it will influence the payoff after completion of the R&D project.

We adopt Kort's modification (Kort, 1998) of Pindyck's model featuring that uncertainty in early phases of the R&D project is usually higher than towards its completion. Only by investing can the firm reduce uncertainty. Another restriction is that the R&D

[31] This can be reached by keeping the long-term concentration of green house gases in the atmosphere at 450 parts per million of CO_2. The current level is about 380 ppm CO_2-eq. Therefore, this scenario is also called the 450 scenario.

[32] The abatement potential in Fig. 3.8 is given in Million ton CO_2. Necessary investments in the energy infrastructure and the energy capital stock are given in Billion USD, 2008 prices.

project is limited to self financing. This is realistic for firms that have market power and are endowed with necessary resources to undertake in-house research projects. While this is certainly a strong assumption, it is for two reasons not unrealistic (see also Kort (1998)). First, if the firm does not depend on external finances, it does not need to unveil information. Thus, it can better capitalise on its advantage in know-how to further strengthen its market position. Second, R&D projects with uncertain outcomes are risky and will therefore lead to higher interest rates if funded externally.

Next, we will introduce the model and derive the optimal investment rule. We will incorporate environmental policies taking the form of energy taxes, energy quotas, and investment subsidies. Later on, the model is extended for a scheme of emission trading.

3.5.2. The model with an extension for energy taxes and quotas

Consider a firm planning to invest in an R&D project that will result in a more energy efficient technology after its completion. As this project needs time to be completed, the firm has to solve a sequential investment problem (sequential call option). We assume that the firm is certain about the outcome of the investment but does not know the cost and time needed to realise this R&D project. The firm can stop the project at any time (option to abandon).

We incorporate solely technical uncertainty understood as uncertainty connected with the creative process, unpredictable challenges, the need for resources, etc[33]. The firm has only an expectation of the actual total cost to completion $\tilde{K}(t)$. The expectation of the total expenditure required to complete the project is denoted by $K(t)$. It holds that $K(t) = \mathcal{E}(\tilde{K}(t))$ with $\mathcal{E}$ being the expectation value operator. The project is completed when the cost to completion reach zero, $K(T) = 0$ with T being the completion time. We follow Kort (1998) in modelling the evolution of remaining investment required to complete the project by

$$dK(t) = -I(t)dt + \gamma(K(t))^{\delta}\sqrt{I(t)K(t)}d\omega(t) \ . \tag{3.26}$$

Again, $I(t)$ is the investment rate and $d\omega(t)$ is the increment of a Wiener process. Parameter γ is a constant and positive parameter. γ denotes overall technical uncertainty. δ reflects the realistic feature of R&D projects that technical uncertainty is larger in early stages.

As stated in the introduction, we assume that the firm carries out an in-house R&D project that is completely self-financed. Thus, investment resources have to be earned by other activities of the firm. Neglecting alternative investment opportunities, the firm has to choose in each investment period between accumulating profits π and investing in the R&D project to realise gains later on from a better energy efficiency. We assume a maximum productive investment rate describing that the project needs time to be completed. The financing restriction for the R&D project is then given by

$$0 \leq I(t) = c\,\pi_0^k(t) \leq \pi_0^k(t) = I_{\max} \quad , \quad 0 \leq c \leq 1 \ . \tag{3.27}$$

[33] See Section 3.1 of this chapter for a detailed discussion of technical uncertainty.

Subscript 0 refers to using the current generation of technology. Superscript k indicates the dependence on environmental policies. We will introduce them later on.

Next, we determine available present and future net profits depending on technology generation $i = \{0, 1\}$. The firm produces an output $q(E, L)$ with inputs of energy E and labour L. The efficiency of an energy-saving technology is described via parameter ϕ_i. This parameter will change to a higher level once the investment project has been finalised. We use a Cobb-Douglas production function with decreasing returns to scale

$$q(E, L) = \theta(\phi_i E)^\alpha L^\beta \text{ with } \alpha, \beta > 0, \ \ \alpha + \beta < 1 \ , \tag{3.28}$$

where α and β are production elasticities of energy and labour. θ is a general productivity parameter. Net profits of the firm depend on output price P, input costs for energy and labour, denoted by z and w respectively, and the environmental policy regime k. We follow van Soest (2005) considering at first two basic types of environmental policies. The first one is a tax regime $k = \mathcal{T}$ with a per-unit-of-energy tax rate τ. The second one is a quota regime $k = \mathcal{Q}$ with a binding, non-tradable quota on the use of energy $\bar{E}$.[34] The firm aims at maximising its profits. Thus, the present and future instantaneous profit flows of the firm are calculated from

$$\pi_i^k(E, L; \phi_i) = \begin{cases} \max_{E,L} \left\{ P\theta(\phi_i E)^\alpha L^\beta - (z+\tau)E - wL \right\} & \text{if } \ k = \mathcal{T} \ , \\ \max_{L} \left\{ P\theta(\phi_i \bar{E})^\alpha L^\beta - z\bar{E} - wL \right\} & \text{if } \ k = \mathcal{Q} \ . \end{cases} \tag{3.29}$$

We assume that the policy will be set once and for all.[35] As the policy does not change, once the R&D project is realised, the firm will be able to produce under the same conditions but with an increased energy efficiency $\phi_i = \phi_1$. In order to compare both policy regimes, we next initialise them with the same level of energy use. The procedure is as follows. First, the government chooses the tax rate equalising marginal benefits and costs of the firm given the current technology ϕ_0. The amount of energy used in this policy regime determines the corresponding energy quota. This quota is therefore a function of tax rate τ. Formally, one has to solve the static profit maximisation problem using the envelope theorem, see the Appendix A.5.1 for details. The energy quota can then be derived as

$$\bar{E} \ = \ \left[P\theta \left(\frac{\beta}{w}\right)^\beta \left(\frac{\alpha}{z+\tau}\right)^{1-\beta} \right]^{\frac{1}{1-\alpha-\beta}} \phi_0^{\alpha/1-\alpha-\beta} \ . \tag{3.30}$$

Profit functions depending on an advanced technology generation $i = 1$ and the initial policy framework can be obtained in a similar way. They are given as

$$\pi_1^k(\phi_1) = \begin{cases} \xi^{\mathcal{T}} \phi_1^{\gamma^{\mathcal{T}}} & \text{for } \ k = \mathcal{T} \ , \\ \xi^{\mathcal{Q}} \phi_1^{\gamma^{\mathcal{Q}}} - z\bar{E} & \text{for } \ k = \mathcal{Q} \ , \end{cases} \tag{3.31}$$

[34] Later on, we will also analyse investment subsidies and emission trading. As the formal introduction is straightforward, we refrain from a derivation.

[35] This assumption will be relaxed in Chapter 4. A discussion of possible time inconsistency problems follows later in this section.

where

$$\begin{aligned}\xi^{\mathcal{T}} &= [1-\alpha-\beta]\left[P\theta\left(\frac{\alpha}{z+\tau}\right)^{\alpha}\left(\frac{\beta}{w}\right)^{\beta}\right]^{\gamma^{\mathcal{T}}/\alpha} , \\ \xi^{\mathcal{Q}} &= (1-\beta)\left[P\theta\bar{E}^{\alpha}\left(\frac{\beta}{w}\right)^{\beta}\right]^{\gamma^{\mathcal{Q}}/\alpha} , \end{aligned} \tag{3.32}$$

with $\gamma^{\mathcal{T}} = \alpha/(1-\alpha-\beta)$ and $\gamma^{\mathcal{Q}} = \alpha/(1-\beta)$.

Knowing present profit functions, subscript 0, and future profit functions, subscript 1, we can determine the optimal investment plan of the firm. To this end, we have to solve the stochastic control problem, Eq. (3.7). Controlling the flow of investments, $I(t) = \{0, I_{\max}\}$, the firm maximises the value of the investment opportunity $F(K(t))$. Introducing a discount rate r, $F(K(t))$ is

$$F(K(t)) = \max_{I(t)} \mathcal{E}_0 \left[\int_T^{\infty} \pi_1^k \exp(-rt)dt - \int_0^T \pi_0^k \exp(-rt)dt\right] . \tag{3.33}$$

The first integral in Eq. (3.33) sums up the discounted cash-flows generated after completing the R&D project. The second integral describes the sum of investments required. Eq. (3.33) is subject to Eq. (3.26), Eqs. (3.31), and $K(T) = 0$. The completion time T of the project is stochastic. As the firm has only an expectation about this value, the present time expectation value operator $\mathcal{E}_0$ acts on both integrals.

As shown in Section 3.3, standard dynamic programming techniques provide a means to derive a critical value K^* for the expected cost to completion. This threshold decides whether or not to invest. In the region where investment is profitable, investment with the possible maximum rate ($c = 1$ in Eq. (3.27)) maximises the value function $F(K)$ in Eq. (3.33). Hence, the optimal investment rule is

$$I(t) = \begin{cases} \pi_0^k & \text{if} \quad K < K^* , \\ 0 & \text{if} \quad K > K^* . \end{cases} \tag{3.34}$$

Only if the expected cost to completion are below the critical threshold K^*, investment at the maximum productive investment rate π_0^k is optimal. The project will be carried out. Otherwise, the firm will refrain from investments.

K^* is a free boundary and can be calculated numerically by solving the following second order ordinary differential equation for $I = \pi_0^k$.[36] We have

$$0 = -1 - \frac{\partial F(t)}{\partial K(t)} + \frac{\gamma^2}{2} K(t)^{2\delta} K(t) \frac{\partial^2 F(t)}{\partial K(t)^2} , \tag{3.35}$$

under conditions

$$F(0) = \pi_1^k / r , \quad \lim_{K\to\infty} F(K) = 0 , \quad F(K^*) = 0 , \quad F'(K^*) = 0 . \tag{3.36}$$

[36] Compare to Eq. (3.12) and its solution by dynamic programming.

Parameter	Value
Technical uncertainty γ	0 .. < 1.4
Technical uncertainty δ	0 .. < 0.5
Energy output elasticity α	0.1 .. 0.5
Labour output elasticity β	0.1 .. 0.7
Total factor productivity θ	1.0
Output price P	1.0
Input price of energy z	0.1 .. 1.0
Input price of labour w	0.1 .. 1.0
Energy efficiency of current technology ϕ_0	1.0
Energy efficiency of future technology ϕ_1	1.2 .. 2.0
Discount rate r	0.05
Per-energy tax rate τ	0 ... 1.0

Table 3.6.: Parameters used in the numerical solution.

The first condition describes the payoff after completing the R&D project. The second one states that for large K it is not reasonable to start the project at all. The two last boundary conditions match the regions of investment and non-investment.

Having all formalities set, we can next analyse how environmental policy and its stringency influence investment decisions. We study how the critical cost for completion K^* depend on the policy regimes. Note that policy enters the problem via Eq. (3.34) and Eqs. (3.36) as the investment rate I and the payoff after completion V are a function of the environmental stringency τ.

3.5.3. Parameter set-up and stability discussion

For a wide range of parameters (see Tab. 3.6), stable and systematic solutions have been found. The functional dependence of the critical costs to completion K^* on policy stringency τ shown in Fig. A.2 is typical. We will use the parameters in that figure as the base case. Note that environmental stringency is given by a tax rate τ from which the equivalent energy quota $\bar{E}$ can be derived. τ ranges between 0.0 and 1.0 implying that environmental policy can double the input price of energy. Such a level has the potential to close the gap between social and private costs in the production of energy (see Section 2.2.1).

In order to study the dependence of K^* on other model parameters, various values have been used keeping the other parameters fixed. Tab. 3.6 gives the range of parameters used in the numerical solution. Note that uncertainty parameters γ and δ are limited to values smaller than $\sqrt{2}$ and 0.5, respectively. Otherwise, a solution for K^* does not exist for the chosen stochastic process. As estimated in Section 3.4, investment projects involving cutting-edge technologies are characterised by $\gamma \approx 0.5$. The efficiency of the future technology for the deployment of energy is described by parameter ϕ_1. In comparison to

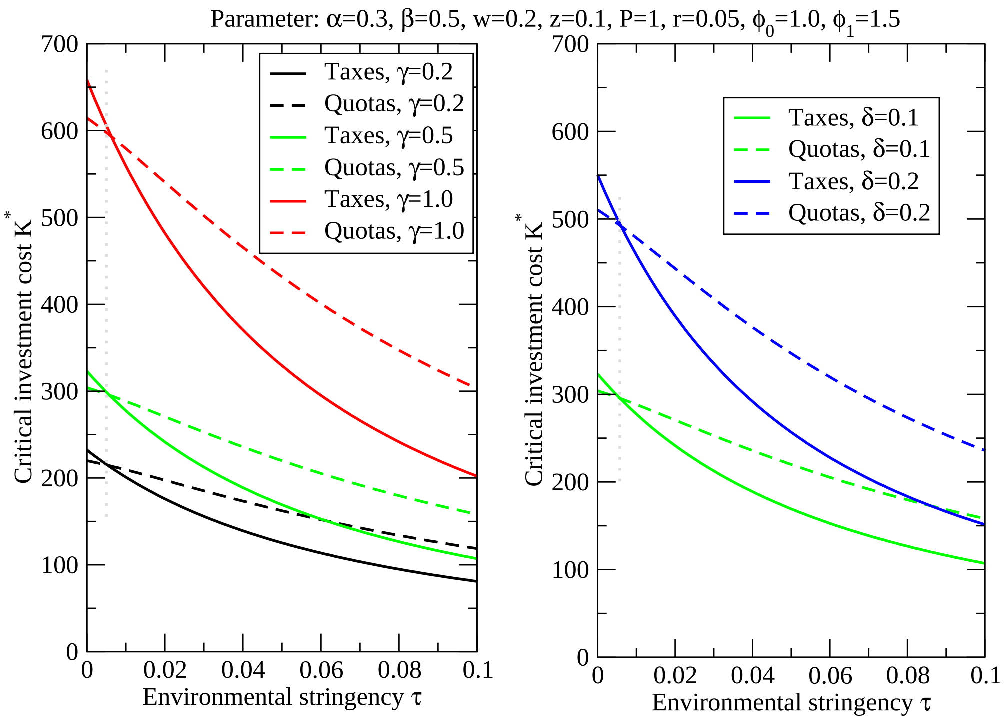


Figure 3.9.: Critical investment cost K^* as a function of environmental stringency τ with dependence on different values for uncertainty parameters γ and δ.

the current available technology ϕ_0, it can increase the energy efficiency up to a factor of two. Output elasticities α and β have also been tested for a broad range. Other parameters are chosen as in the set-up used for a model studying the optimal timing of technology adoption by van Soest (2005).

3.5.4. Results from the real options model

Investment is only profitable if the expected cost to completion K is smaller than K^*. Therefore and in general, the higher K^*, the better the investment conditions are.

As a first result, the numerical survey suggests a universal behaviour of the functional dependence of K^* on the stringency of environmental policy τ. When τ increases, K^* decreases. Thus, the less stringent the environmental policy is, the better the conditions for the firm to invest (see Fig. 3.9). Environmental policy reduces profits making less resources available for investing and more time necessary to develop the technology with an improved energy efficiency. As a consequence, future payoffs also shrink.

One might expect that the difference between the tax and the quota regime disappears for $\tau \to 0$, but this is not the case. Fig. 3.10 illustrates this fact. As long as the current technology ϕ_0 is in use, the optimal amounts of energy and labour are the same in both regimes, i.e. $ET(\phi_0) = EQ(\phi_0)$ and $LT(\phi_0) = LQ(\phi_0)$. However, when the new technology ϕ_1 is available, the firm increases its input of energy under taxes to $ET(\phi_1)$

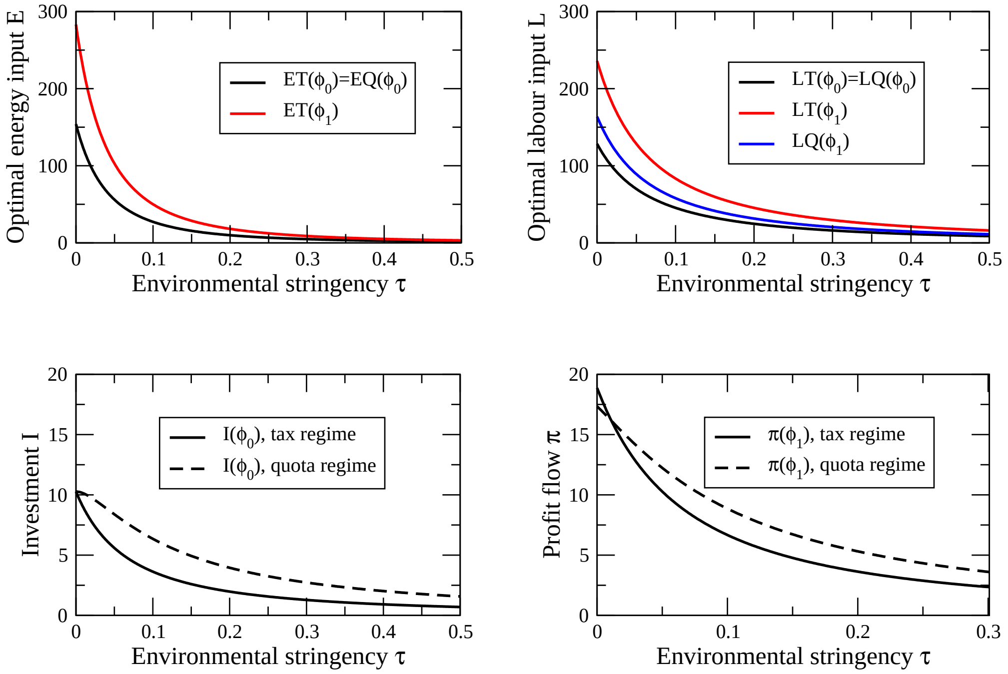


Figure 3.10.: Optimal inputs of energy ET and labour LT under taxes and quotas EQ, LQ, as well as resulting investment resources I and profit flows π.

(upper left graph). The input of labour will be augmented in both regimes but higher in the more flexible tax regime, i.e. $LT(\phi_1) > LQ(\phi_1)$ (top right graph). Note that the gap between the inputs in the two regimes closes with an increase in τ. The optimal choice of inputs defines the resources available for investments $I(\phi_0)$ and thus the time needed to realise the R&D project. For any $\tau > 0$, the firm can investment more in the quota regime (lower left graph) since the lack of an energy tax to be paid means that input costs of energy are smaller by the amount of $\tau E(\tau)$, see Eq. (3.29). However, while the initialization of the policy regimes favours the quota regime at the start, when technology ϕ_1 becomes available, the tax regime allows the firm to better adjust its inputs explaining the higher profit flows $\pi(\phi_1)$ for small τ (lower right graph). But the advantage of higher inputs melts rapidly with τ as energy input cost climbs with $\tau E(\tau)$. This leads to an intersection of the profit flows in the two regimes at low stringencies. The point of intersection is below 0.1 for all parameter ranges. As a consequence, the K^*-γ graphs for the tax and the quota regime also intersect.

We shall now go into more detail to provide a better intuition on the effect of environmental policy. Fig. 3.11 shows the optimal input of energy chosen by the firm under the old (black line) and under the improved technology (red line) as a function of environmental stringency τ. In the absence of environmental policy, the optimal input of energy is E_0. When an environmental policy is introduced, the firm lowers its input of energy to E_1. If the firm now invests into a better technology, less energy would be needed to

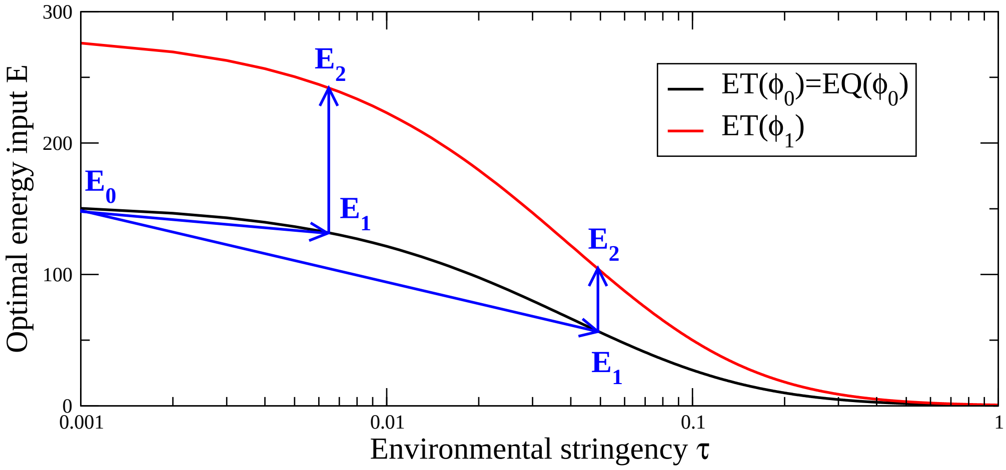


Figure 3.11.: Optimal input of energy as a function of environmental stringency τ and technology generation $i = \{0, 1\}$.

produce the same amount of output. This cheaper way of production is the motivation for the firm to invest in R&D. In the tax regime, the firm additionally benefits from increasing its input of energy to E_2 once the new technology is available. Note, that this additional benefit decreases with τ. For the first choice of τ considered in the figure, E_2 is even greater than E_0 resulting in no environmental benefit from introducing the policy. Yet, this depends on the level of environmental stringency. As you can see from the second example in Fig. 3.11, E_2 is smaller than E_0. Thus in this case, environmental policy induces an emission reduction. However, as E_1 will always be smaller than E_2, we observe a partial rebound effect (see Fig. 3.12).

Returning to Fig. 3.9, it can be seen that K^* strongly depends on γ and δ. Fig. A.2 shows in addition the results for the deterministic case, $\gamma = \delta = 0$. As both figures illustrate, K^* increases with γ and δ. For example, if the price for energy is doubled, K^* increases in the tax regime from 75 ($\gamma = \delta = 0$) to 107 ($\gamma = 0.5, \delta = 0.1$), while in the quota regime, K^* increases from 110 to 158. By investing the firm can reduce uncertainty and is rewarded with a better understanding about the remaining cost required to complete the project. The larger the amount of uncertainty, the more of it can be resolved by learning. Thereby, a shadow value for completing the project is created. Furthermore, if τ is low, the firm has larger investment resources and hence can learn more. Note that this result depends on the type of uncertainty. Output price uncertainty, for example, reduces K^* and generates a value of waiting.

As discussed above, taxes dominate quotas only if the level of environmental stringency is small. The intersection between both regimes is thereby not strongly dependent on variations in the parameters α, β, γ, δ, z, and ϕ_1 (Figs. 3.9, A.2, A.3, A.4). More important is the finding that K^* and α are positively correlated; the smaller the elasticity of the energy output α, the less investment resources and future payoffs are affected. K^* is most sensitive to changes in the market price of energy z and in the future technology

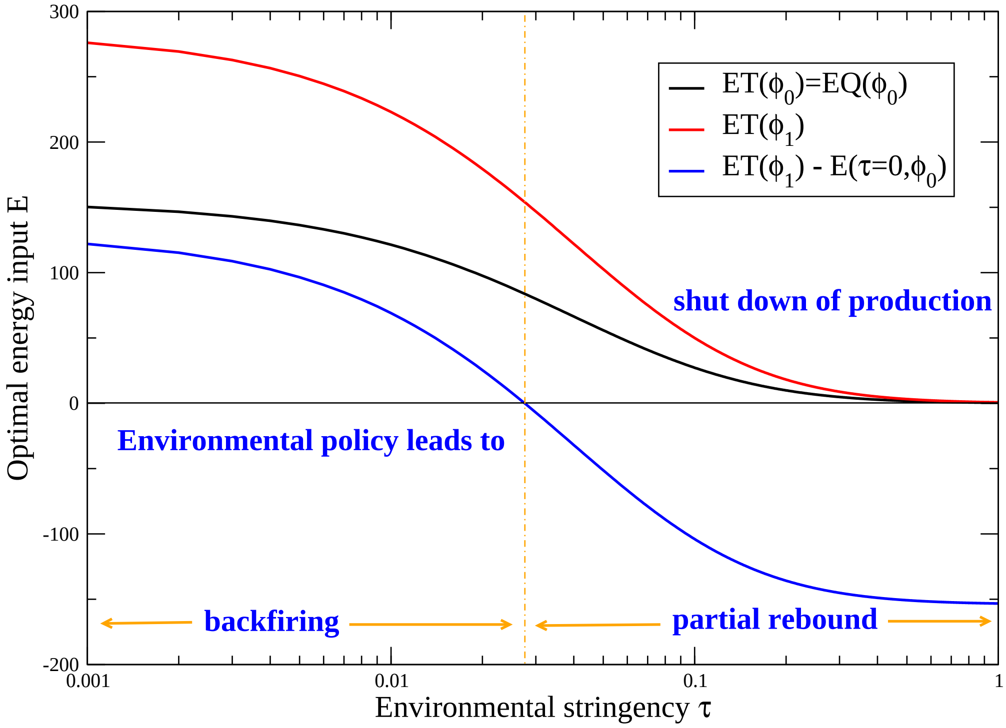


Figure 3.12.: Magnitude of rebound effect as a function of environmental stringency τ.

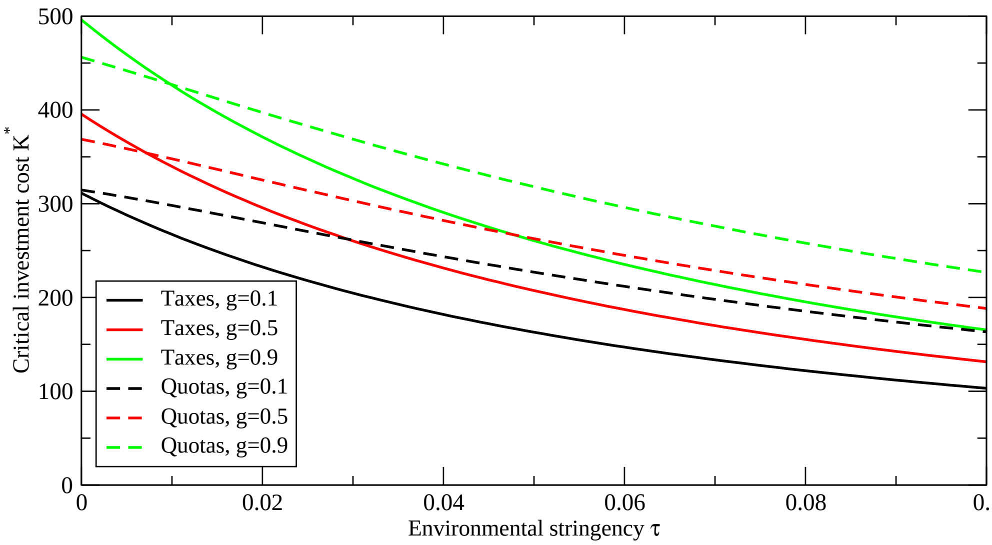


Figure 3.13.: Critical cost to completion K^* as a function of the environmental stringency τ and the investment grant rate g.

ϕ_1. It is not surprising that an increase in ϕ_1 induces K^* to rise, whereas a higher z causes K^* to fall.

How do investment conditions change if investments are subsidised with a grant rate denoted by g? This can be answered by replacing I with $(1-g)I$ in Eq. (3.33) and with $\pi_0^k/(1-g)$ in Eq. (3.34), the upper constraint for the maximal investment rate. Fig. 3.13 illustrates the result. Investment subsidies induce an increase in K^*. This is because an investment grant implies that the firm can invest more, and thus the investment rate can be increased. Therefore, the effect goes beyond a simple reduction of investment costs. Though, this would not be the case if the firm could not *productively* invest more (see also Kort (1998)).

3.5.5. Extension to emission trading

Recently, emission trading schemes have been implemented as an alternative or complementary measure to provide incentives for the reduction of e.g. green house gas emissions. An example is the European Union Emission Trading Scheme introduced in 2005 (see e.g. Hoffmann et al. (2008)).

We introduce the following simple scheme. The government freely distributes initial permits for the use of energy. In the case that the firm wishes to expand its energy use beyond what is permitted, the firm can purchase the additional amount at a permit price z_{cap} per unit of energy. Selling redundant amounts is also possible. Under the assumption that emission trade markets are perfectly competitive, firms are price-takers. To keep the model simple, the permit price is fixed and trading costs are neglected. For comparing the three policy regimes (taxes, quotas, emission trading), we choose all parameters in such a way that the firm's optimal amount of energy is initially the same in all regimes. This means, the permit price is set at the level of the tax rate τ, and the cap on the input of energy $\bar{E}^{\text{cap}}$ is chosen to equal the optimal amount of energy in the quota regime. Thus, the use of energy is the same in all regimes until the new technology ϕ_1 has been developed. It is implied that initially the firm will neither buy nor sell emission allowances. Only after completing the R&D project will the firm adjust its inputs L and E. Future instantaneous profit flows in the cap-and-trade regime π_1^{cap} are derived in a similar procedure as in the two other regimes. Eqs. (3.29) and (3.32) are given for the cap-and-trade regime as

$$\begin{aligned} \pi_1^{\text{cap}}(E, L; \phi_1) &= \max_{E,L} \left\{ P\theta(\phi_1 E)^\alpha L^\beta - zE - wL - z_{\text{cap}}(E - \bar{E}^{\text{cap}}(\tau)) \right\} \\ &= \xi^{\text{cap}} \phi_1^{\gamma^{\text{cap}}} + z_{\text{cap}} \bar{E}^{\text{cap}}(\tau) \ , \end{aligned} \tag{3.37}$$

with

$$\xi^{\text{cap}} = [1-\alpha-\beta] \left[P\theta \left(\frac{\alpha}{z + z_{\text{cap}}} \right)^\alpha \left(\frac{\beta}{w} \right)^\beta \right]^{\gamma^{\text{cap}}/\alpha} , \tag{3.38}$$

where $\gamma^{\text{cap}} = \alpha/(1-\alpha-\beta)$. z_{cap} denotes the equilibrium permit price. Note that $\bar{E}^{\text{cap}}$ is a function of the policy parameter τ. Next, we solve Eqs. (3.35-3.36) using Eq. (3.37).

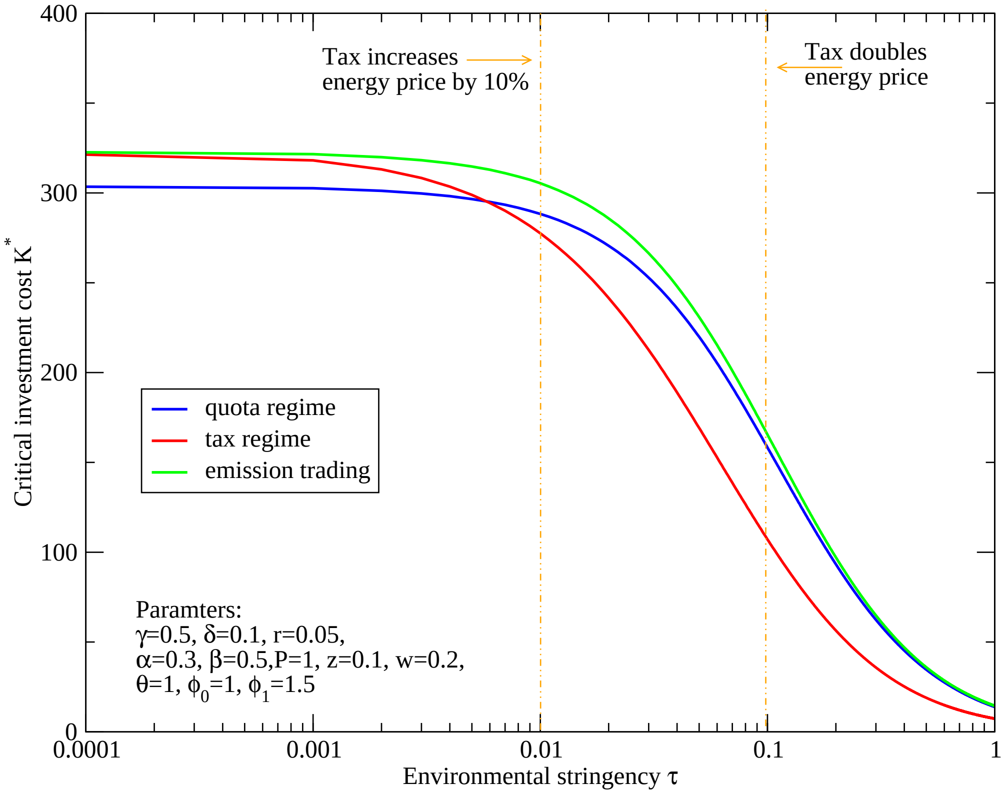


Figure 3.14.: Critical investment cost K^* as a function of environmental stringency τ for the tax regime, the quota regime, and the emission trading regime.

Fig. 3.14 shows the results for the cap-and-trade regime compared to the quota and the tax regime. We find again that K^* decreases with environmental stringency implying that the region where investment is profitable shrinks. Environmental policy imposes costs on the firm. It has to pay energy taxes or it is restricted to a certain amount of energy and extra energy costs money. Thus, less resources are available for investing, and less pay-off can be generated after the project's finalisation. In the extreme, the firm will choose to freeze its production (compare Fig. 3.12). What is the ranking of the three policy regimes? We find that emission trading always leads to a higher critical threshold for investment, K^*. For example, K^* increases by 5% in comparison to the quota regime at $\tau = 0.1$. The firm under the emission trading regime can realise the relative advantages of the tax as well as the quota regime. It can proceed as quickly with the R&D project as in the quota regime plus it has the flexibility to expand its use of energy under the new technology by purchasing additional permits. This is illustrated in Fig. 3.15. Finally, the dashed brown lines in Fig. 3.14 indicate a realistic range for the level of environmental stringency τ. A $\tau = 0.01$ implies that the energy tax raises the energy price by 10%. A $\tau = 0.1$ implies that the energy price is doubled. In this range the ranking of the three policy regimes is unambiguous: emission trading performs best

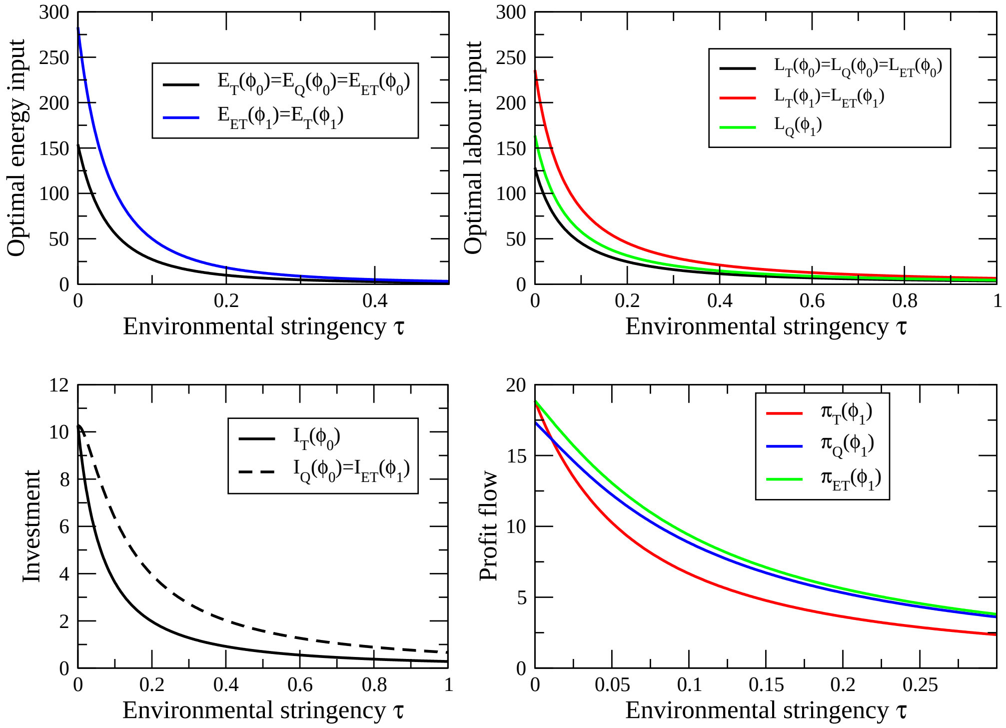


Figure 3.15.: Optimal inputs of energy and labour in the tax regime (T), in the quota regime (Q), and in the cap-and-trade regime (ET).

followed by quotas.

Environmental policy thus implies an increase of energy costs potentially closing the gap between related external and social costs. However, this is paid for dearly as incentives to invest in energy-saving technologies are diminished. This disadvantage could be avoided by granting R&D subsidies.

3.5.6. Limitations and conclusions

We have studied the impact of environmental policies on optimal R&D investment plans of a single firm. The firm makes its investment decision under technical uncertainty and irreversibility. The central findings are

- Investment in energy-saving technologies increases with technical uncertainty. This is due to the fact that only by investing can the firm learn about the remaining cost to completion. This finding is in line with other literature, e.g. Kort (1998).
- Taking account of technical uncertainty $\gamma = 0.5$, critical investment costs increase by 43 % for the tax and 44 % for the quota regime. This example holds for the case that environmental policy doubles the price of energy.

Parameter	Impact on K^*
Technical uncertainty γ	++
Technical uncertainty δ	+++
Energy output elasticity α	++
Labour output elasticity β	+
Input price of energy z	- - -
Future technology for deployment of energy ϕ_1	++
Environmental stringency τ	- - -
R&D investment grants g	++
Equilibrium permit price z_{cap}	- -

Table 3.7.: Impact of selected parameters on the sum of critical investment costs in relation to the base case (Fig. A.2). Signs imply: +/- moderate impact on K^*, ++/- - strong impact on K^*, +++/— decisive impact on K^*.

- The more stringent environmental policies are set, the less the incentives to invest in R&D as investment resources and future payoffs are reduced.
- Granting R&D subsidies is a countermeasure.
- Among the three environmental policy regimes, emission trading performs best in terms of inducing energy-saving R&D. The firm can flexibly choose its inputs with the additional option to buy emission permits.
- The advantage of the cap-and-trade regime amounts to approximately 5 % relative to the quota regime in the case that environmental policy doubles the energy price and the equilibrium permit price equals the energy price. The firm will choose to buy additional permits.
- The ranking of the tax and the quota regime is ambiguous. Only for very low levels of environmental stringency do taxes dominate quotas. For these levels of environmental stringency τ, the firm can additionally benefit from expanding its inputs under the new technology. However, this benefit decreases with τ. At the point of intersection, the advantage is no longer big enough to balance the higher energy taxes which the firm does not have to pay under the quota regime. Model parameters influence foremost the slope. The intersection point between the two regimes is much less sensitive to parameter changes. Table 3.7 summarises the qualitative results for the comparative statistics.
- In a realistic range for the level of environmental stringency, the ranking of the three policy regimes is unambiguous: emission trading performs best followed by quotas.

Several assumptions were made. First, we concentrated on the impact of environmental policy on a single firm. Doing so, we neglected aspects of competition and knowledge spillovers. The former can provide incentives to accelerate investments, whereas the latter slow them down. Second, we have assumed that the decision to perform R&D does not depend on financing resources. This simplification is realistic for established firms that exercise strong market power and have excess to sufficient financing resources (see also the discussion in Section 3.3.4.). As a possibility for future research, the model can be extended to include auctioning. Finally, we have assumed that environmental policy once set does not change. In doing so, we assume that policy institutions are myopic; a commitment problem does not exist. However, time consistency can be an unrealistic assumption since an ex-ante optimal policy might be ex-post less favourable. For example, once firms have invested, the government can turn towards other objectives. This can imply changing policies, e.g. taking back taxes in order to give national firms a competitive advantage in international markets. Then results would depend upon the ability of firms or policy institutions to anticipate changes and adopt their optimal strategies accordingly. However, institutional and legal obligations build natural barriers against rapid changes. Hence, the assumption of continuing a certain policy stringency level can hold at least for short- and medium-term projects. Implications if two uncertainties are present, technical and policy uncertainty, are explored in the next chapter.

3.6. Chapter summary

We have studied the implications of irreversibility and technical uncertainty on the R&D investment decisions of a single firm using the sequential investment model with the option to abandon, developed by Pindyck (1993). Dynamic programming techniques and Monto Carlo simulation have been applied to solve and extensively discuss the model. Results confirm that technical uncertainty raises the critical threshold for investment costs, adding a value to the R&D project in comparison to the case of certainty. An increase in the payoff from completing the project increases the value of investing. An increase in the risk-less discount rate and the maximum productive investment rate shrink the region for investment. But the impact of the latter is less sensitive to higher investment rates. We furthermore found that the risk for non-profitable investments increases exponentially when approaching the border between the regions of investment and non-investment.

The model was extended for environmental policies, feed-in tariffs, to study the investment decision in offshore wind parks by large energy corporations. Germany's first commercial offshore farm, Baltic 1, served a case study. Apart from technical uncertainty, uncertainty related to cash-flows from the project were included by considering a corridor for expected operation and maintenance costs. Multiple regressions of data for different European offshore parks were performed, resulting in the finding that expected investment costs amount to about 135 MEUR / 140 MEUR depending on the distance from shore. Technical uncertainty was estimated to be about $\gamma = 0.5$. This magnitude induces the critical threshold for the expected investment cost to increase by 12 %. Results furthermore showed that under the German Renewable Energy Resources Act of 2009, Baltic 1 can be run profitably. However, the guarantee of a sprinter bonus is crucial. Under this regime, risks of non-profitable investments are not higher than 9 %.

A third modification to the model was made to study the influence of environmental as well as technology policies on the decision of a single firm to develop an energy-saving technology. We analysed Pigouvian energy taxes, energy quotas, R&D subsidies, and a scheme for emission-trading. The central finding was that investment in energy-saving technologies will increase with technical uncertainty. In fact, the critical threshold for expected investment cost increases by more than 40 %. This holds even if environmental policy doubles the input costs for energy. However, more stringent environmental policies hamper R&D investments. This can be balanced out by granting investment subsidies. Among other model parameters, the efficiency parameter of the new energy-saving technology and the energy output elasticity also positively influence the critical threshold for expected investment cost. However, the input price of energy and the equilibrium permit price have a negative impact. When ranking environmental policy regimes, emission trading performs best in terms of inducing energy-saving R&D. The ranking of the tax and the quota regimes are ambiguous. Only for low environmental stringency will taxes dominate quotas.

Despite limitations, generic features of R&D have been incorporated into our models. They allowed us to elucidate the dynamics of investment decisions of a monopolistic firm under the influence of environmental policies.

4. R&D investment under technical and policy uncertainty

4.1. Motivation

Due to market failures and inefficiencies of the innovation system connected with the production of knowledge and environmental externalities, the level of green R&D investments is below its potential. Governments apply various incentive measures to overcome investment barriers and to direct the development of technological change, such as the provision of investment grants or the imposition of environmental taxes and quotas. Thus, a firm's investment decision also depends on environmental policy parameters in addition to organisational and financial resources, prospective cash-flows, and scientific challenges.[1] But environmental regulations are likely to be subject to substantial uncertainty.

Reasons for policy uncertainty are various. Some are related to governmental learning. It might, for example, become necessary to adjust policies with the arrival of new information, e.g. after an evaluation yields the result that a regulation is not efficient. Coming to a better understanding of the impacts of environmental damages and associated costs is another example for adjustments in policy. But environmental policy uncertainty can also be caused by changes in other policy areas switching regulative priorities. Fig. 4.1 illustrates the frequent adjustments of taxes in Germany that are imposed on the use of fuels (introduced in 1951) and the use of electricity (introduced in 1999). It can be seen that these environmental taxes have changed within relatively short periods compared with the time horizon of many research projects. Additionally, increases in taxes can be large. For example, the tax rate for the use of electricity in the industrial, agricultural, and forestry sectors was sextupled within 5 years from 2.05 EUR/MWh to 12.3 EUR/MWh.

Apart from environmental regulation via taxes, quotas, or legislation, incentives in form of R&D subsidies (e.g. as project grants) are also subject to uncertainties. Besides the reasons for policy changes stated above, governmental R&D programmes are typically installed for only a couple of years. Their aim is to foster particularly short- and mid-term investment behaviour. It is furthermore not known if such a programme would be continued or how funds would be allocated, e.g. for the promotion of eco-innovations. These decisions are often only made after long negotiations with stake-holders and interest groups. Therefore, uncertainty about the availability of subsidies can strongly affect the planning of long-term R&D. Fig. 4.2 shows the development of selected energy

[1] See also Section 2.1 for findings in the literature on policy as a factor in green technological progress.

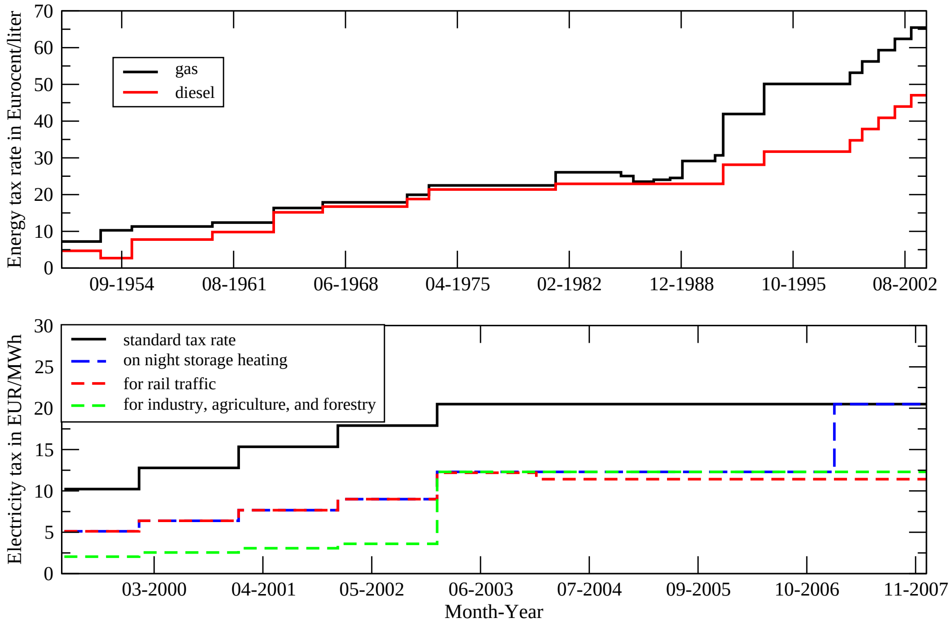


Figure 4.1.: Development of energy and electricity taxes in Germany. Source: BMBF, 2010; www.bundesfinanzministerium.de.

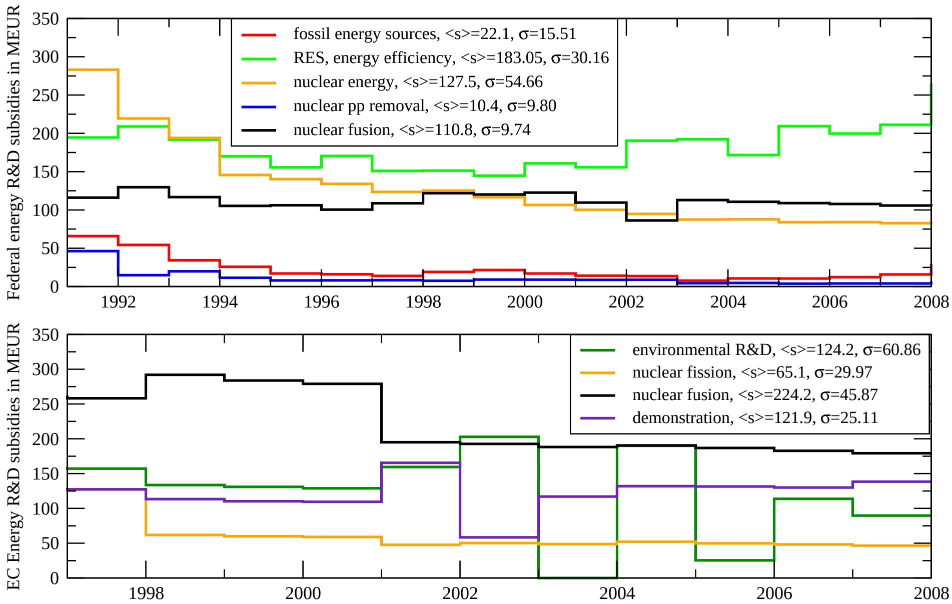


Figure 4.2.: Development of selected R&D subsidies, national and European funds. Source: BMBF, 2010; www.bmwi.de.

R&D subsidies from national (1991-2008) and European programmes (1997-2008). As the data illustrate, the allocation of funds is not at all exclusive to environmental R&D as large sums are directed to fusion and fission R&D. In the case of national funds, on average 183 MEUR have been spent annually on R&D of environmental technologies. The focus of the German government was on the development of renewable energy resources (RES) and a more efficient deployment of energy. At the EU level, R&D funds under the directive of DG Research supported foremost project proposals related to fuel cells, energy sources, energy transport, energy storage (in particular hydrogen), renewable energies, CO_2-capture, and socio-economic interdependencies. Research under the directive of DG TREN supported demonstration measures for renewable energies, eco-building, polygeneration (e.g. combined heating and electricity), and alternative fuels. An average of 124 MEUR (DG Research) and 122 MEUR (DG TREN) have been spent annually. However, funds strongly fluctuate with standard deviations of 61 MEUR and 25 MEUR respectively. In the case of funding from DG Research, support even dropped to zero in 2004.

Certainly, policy uncertainty impacts the investment decision in addition to technical uncertainty. In this chapter we extend the models from Chapter 3 to include both, and we will study how this influences the optimal R&D decision of a single firm. After a short review of the real options literature that considers policy uncertainty, we introduce our approach to formalise this type of uncertainty. Two models with two different types of uncertainty will be developed, i.e. uncertain R&D investment grants and uncertain quotas and taxes on the use of energy.

4.2. Review of real options literature considering policy uncertainty

In the last decade, the literature studying the impact of policy uncertainty on a firm's investment decision has been steadily growing; see Niemann and Sureth (2008) for a review. Most contributions focus on policy uncertainty in general (Hassett and Metcalf, 1999; Böhm and Funke, 2000; Agliardi, 2001; Pawlina and Kort, 2005; Hoffmann et al., 2008; Alvarez and Koskela, 2008; Niemann, 2010). Uncertainty of environmental policy is considered in Larson and Frisvold (1996); Farzin and Kort (2000); Isik (2004), and Baker and Shittu (2006). To the best of our knowledge, this thesis is the first to combine uncertainty about the technical advance of a sequential R&D project and (environmental) policy uncertainty.

Investment tax credits for new capital, i.e. implicit investment subsidies, are studied in the seminal contribution of Hassett and Metcalf (1999). They model the evolution of after tax returns allowing taxes to switch randomly between a high and low level. Policy changes are assumed to be mean-preserving by linearly relating the Poisson distributed arrival rates to output price realisations. Hassett and Metcalf (1999) find that in times of high capital costs (low tax credits) the incentive to postpone investments increases; it is optimal to wait for the likely up-coming improvements. Likewise, investments are accelerated if capital costs are low. The authors find that the impact of policy uncertainty depends on the assumed stochastic process. Using a geometric Brownian motion, an increase in uncertainty hampers investments, but a stationary jump process can also result in an acceleration of investments. The latter finding opposes the conjectured truism that greater policy uncertainty is counterproductive for investments. This is the starting point of Böhm and Funke (2000) who assume demand uncertainty (Brownian motion) and changes in investment credits. The latter follow a continuous-time Poisson process switching between a high and a low level, as in Hassett and Metcalf (1999). Hence, the resulting value function for the investment opportunity depends on a combined Brownian motion-jump process. Numerical results support the general wisdom insofar as the impact of tax uncertainty on the optimal investment decision is very small. Therefore, tax uncertainty should neither be 'blamed' for a hesitant investment behaviour nor will a policy that aims to reduce tax uncertainty be a 'magic bullet'.

Agliardi (2001) analyses the interplay of uncertainty in the price of the capital stock (Brownian motion) and uncertainty about future operating cash-flows. The price of the capital stock is furthermore subject to discrete jumps caused by changes of investment grants (Poisson arrival). The effect of uncertainty about changing investment grants is ambiguous, but the higher the arrival rate, the lower the critical investment threshold is. Hence, with increasing policy uncertainty, investments slow down. Niemann (2010) confirms that the impact of uncertainty on investment tax credits is ambiguous. The author models uncertainty as an arithmetic Brownian motion which is not perfectly correlated with cash-flow uncertainty[2]. Niemann (2010) finds that investments are accelerated if uncertainty about the cash-flow and its correlation with policy uncertainty are high.

Pawlina and Kort (2005) study the impact of uncertain and discrete 'structural changes', e.g. caused by tax policies. They assume that the value of an investment project follows a geometric Brownian motion and a structural change happens if it reaches some trigger value. The firm is uncertain about the trigger value but expects a higher probability for changes to occur in booming times. This will cause investment costs to jump to an uncertain, higher level - e.g. when investment tax credits are cut. The new feature in their model is that the structural change does not arrive at a constant rate over time as is assumed with Poissonian distributed arrivals. In the case that a jump in investment costs is likely, Pawlina and Kort (2005) obtain that it is optimal to invest just before the change occurs. Uncertainty about the trigger value that causes the change has an ambiguous impact. Initially, as long as uncertainty is still small, the critical project value that induces investments decreases. Thus, earlier investments are optimal. However, if uncertainty continues to grow, this critical value increases and investments are postponed. Pawlina and Kort (2005) furthermore find that a policy aiming to encourage investments should abstain from using uncertainty as a policy instrument. Otherwise, the average expected time to invest diminishes by 23 %. A similar result is obtained by Isik (2004) who studies the impact of cost-share subsidies on the decision to adopt site-specific technologies for more environmentally-benign farming.[3] Again, investments

[2] If both are perfectly correlated, then tax uncertainty is never independent from cash-flow uncertainty since they would be linearly related.

[3] See also the review in Section 2.3.

are accelerated just before an expected worsening of the investment conditions.

There are a few contributions that analyse the impact of uncertain taxes. Larson and Frisvold (1996), Farzin and Kort (2000), and Baker and Shittu (2006) study the case of environmental taxes. A linear progression of taxes and tax exemptions are analysed by Alvarez and Koskela (2008) and Niemann and Sureth (2008). The contributions considering environmental taxes have been reviewed in Section 2.3. Here, we only report the general result: uncertainty about environmental policies tends to slow down investments. However, the better a firm is able to realise advantages from investing in abatement measures, the smaller the effect of postponing investments. This can be the case if the firm expects a cut of policy support to come soon (e.g. a reduction in cost-share subsidies) or an upcoming tightening of environmental taxes or standards. Better adjustment possibilities of the firm (e.g. a high substitutionability of polluting inputs) promotes investments in the same way.

Alvarez and Koskela (2008) analyse the implications of an uncertain linear progression of an interest income tax and the possibility of a tax exemption. The result of the irreversible investment model is the following. If the threshold for tax exemption is below the sunk investment costs, investment decreases, because the net-of-tax payoff decreases. But if the tax exemption threshold is larger than sunk investment costs, then three different outcomes are possible. If, 1), the tax volatility is low, the optimal exercise threshold increases and thus, investment decreases. However, the tax rate does not affect the optimal policy. If, 2), the volatility increases up to the point where the critical value for investment equals the level of tax exemption, then the optimal investment policy is independent of the tax rate and its volatility. If, 3), the volatility of the tax rate increases beyond this critical level, then the optimal investment policy becomes a function of the tax rate (negative relationship) and the volatility (positive relationship). This 'tax paradox' is a result of the possibility of tax exemption. Tax exemption provides a shield against risks.

Most studies have shown, policy uncertainty tends to slow down investments. However, the magnitude of the effect depends on the possibility of a firm to hedge against future risks. Furthermore, the process best used to describe the development of uncertain policy parameters is open to discussion. Relating the trigger of policy changes to other model parameters and/or allowing for time-dependent arrival rates represent potential areas for development.

4.3. Concept and formalisation of policy uncertainty

4.3.1. Uncertain R&D subsidies

The question we concern ourselves with here is how policy uncertainty at the aggregate level, as illustrated in Fig. 4.2 translates to policy uncertainty at the firm level. We will consider R&D subsidies and assume that an R&D programme has just started. In this case, it is foremost the duration of possible project support that is uncertain. For example, a typical funding time of an R&D project is 3 years. In addition, there is often the possibility to extend the project for another 1-3 years depending on the demand for total subsidies and remaining programme funds, although the maximum prolongation is limited by the running time of the programme, typically 5-10 years.[4] This causes uncertainty about the duration of financial support for the project. It is furthermore typical that programmes have a standard reimbursement rate of 50 % for the private sector. Small- and medium-size enterprises can receive up to 75%.

We will use a Weibull distribution (Weibull, 1951) to model uncertainty of the timing of R&D subsidies. The advantage of a Weibull distribution is that it allows for time-dependent arrival or failure rates. We will consider two scenarios. First, we study the effect when an R&D programme has just started and it is uncertain how long the subsidies will be granted to the firm undertaking the R&D (switch-off regime). We assume that the average support for a project is 3 years. This defines the expectation value of the distribution. Furthermore, it shall not be very likely that the support would be already stopped before this average funding time. This implies that the maximum value of the distribution is reached comparatively quickly. But afterwards, the probability to receive further financing decreases relatively slowly over time until year seven when it is almost zero, coinciding with the end of the funding programme. This assumption defines how to choose the parameter describing the slope of the Weibull distribution. Secondly, we study the effect when an R&D programme is still in the phase of planning and has not yet been started. Here, a firm planning to start a project is now uncertain about the actual time when funds will be available (switch-on regime). We assume that the probability is high that subsidies will become available within the next two years. This defines the expectation value of the second distribution. Furthermore, the probability that the programme start would be postponed for more than 3 years shall be low.

The Weibull distribution for a random variable T_C, i.e. the time at which the policy change occurs, and its expectation value $\mathcal{E}_{\mathrm{wb}}(T_C)$ are defined by

$$\begin{aligned} f_{\mathrm{wb}}(T_C) &= \alpha\,\beta\,T_C^{\beta-1}\exp(-\alpha T_C^{\beta}) \;, \qquad (4.1) \\ \mathcal{E}_{\mathrm{wb}}(T_C) &= \alpha^{-1/\beta}\,\Gamma(1+\beta^{-1}) \;, \qquad (4.2) \end{aligned}$$

where $\alpha > 0$ is the scale parameter, $\beta > 0$ the shape parameter, and $\Gamma()$ is the Γ-function (Abramowitz and Stegun, 1972, p. 253-294). The considerations made above about the policy regimes are best fit by the following parameters. For the switch-off regime, we

[4] An important source for project grants to carry out energy R&D in Germany is the Federal Energy Research Programme (BMWi, 2005). The 5th programme period ran from 2003-2008. Currently, the follow-up programme is in preparation, including discussions with stake-holders (e.g. Helmholtz-Gemeinschaft (2009); Leopoldina (2009); Frauenhofer (2010)) and fine-tuning. The new national energy concept is due in October 2010. The 6th Energy Research Programme is planned to start in mid 2011. According to press releases, it is expected that more finances will be available for 1) R&D of energy storage technologies, 2) re-modelling of energy networks, and 3) project grants. At the EU level, the Research Framework Programmes provide grants for R&D. For example, more than 50 Billion EUR are available in 'key thematic areas'. Among these are 'energy' and 'environment (incl. climate change)'. EU Funding Programmes support projects on average between 3-5 years. In some cases, the project can be extended. The current funding period started in 2007 and ends in 2013. Negotiations with member states about the up-coming 8th programme period have started in 2009. See e.g. http://ec.europa.eu/research/fp7/pdf/fp7-inbrief_en.pdf.

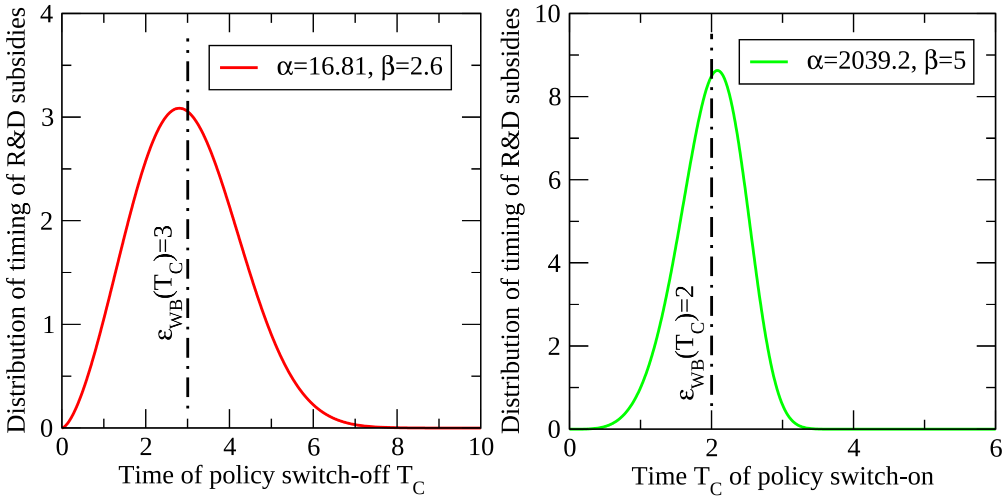


Figure 4.3.: Left-hand side: Weibull distribution for the policy switch-off regime. Right-hand side: Weibull distribution for the policy switch-on regime.

chose $\alpha = 16.81$ and $\beta = 2.6$. The switch-on regime is modelled by $\alpha = 2039$ and $\beta = 5$. The resulting realisations for the Weibull distribution are illustrated in Fig. 4.3.

The variance of the Weibull distribution is also known analytically to be

$$\mathcal{V}ar(T_C) = \alpha^{-2/\beta}\left(\Gamma(2\beta^{-1}+1) - \Gamma(\beta^{-1}+1)^2\right) \quad . \tag{4.3}$$

4.3.2. Uncertain taxes and quotas on the use of energy

From Fig. 4.1 it can be seen that the tax rate on the use of energy in Germany has been frequently changed since its introduction in 1999. The last change however occurred in 2002. Following the current discussion in Germany about the upcoming new energy concept, one might expect that the probability of a new adjustment in the near future is high. We take this conjecture as the starting point for our next analysis of the effect of policy changes on the optimal decision of a firm to invest in environmental R&D. As policy instruments, we will consider a per-unit energy tax and a quota on the use of energy.

Uncertainty about the timing of a policy change at T_C is modelled using a Weibull distribution, Eq. (4.1). Parameters α and β are chosen to fit the expectation that a change in policies occurs within 1 year or 2 years after the start of an R&D project, see Eq. (4.2). The appropriate choice of parameters is $\alpha = 819.52$, $\beta = 5$ and $\alpha = 25.61$, $\beta = 5$, respectively. Resulting Weibull distributions are illustrated in Fig. 4.4. The left graph in this figure furthermore includes a Weibull distribution with constant arrival rates, i.e. $\alpha = 8.33$ and $\beta = 1$. α is chosen to fit an expectation value of $\mathcal{E}_{\mathrm{WB}} = 12$ months. We use this particular representation of a Weibull distribution to analyse the effect of constant versus time-dependent arrival rates.

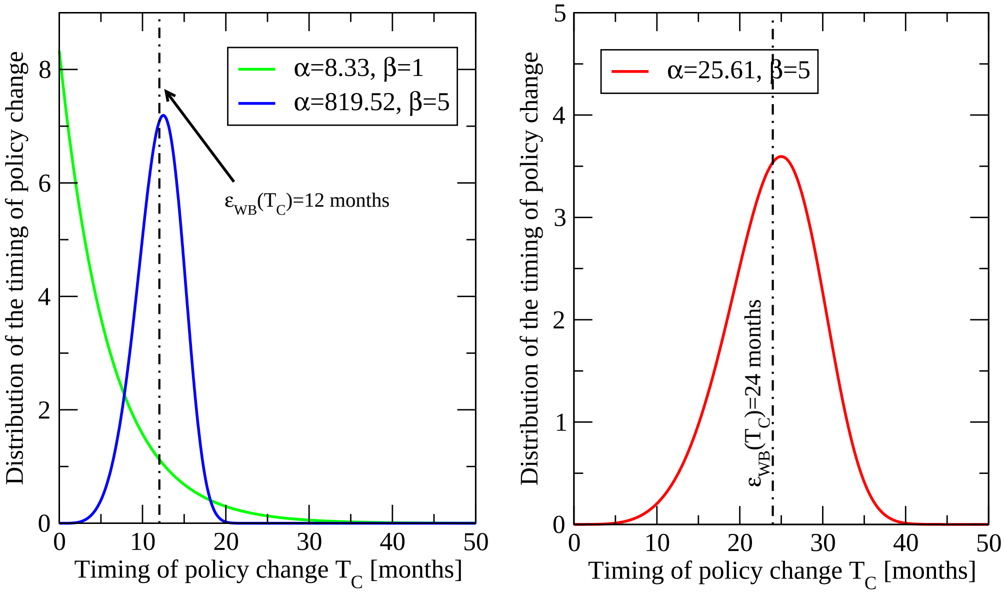


Figure 4.4.: Weibull distributions for a policy regime with an uncertain timing T_C for a change in environmental stringency τ.

4.4. Application: uncertain R&D subsidies

4.4.1. The model and its solution

We extend the basic model accounting for technical uncertainty from Section 3.3 by adding uncertainty of the timing of investment grants. A firm plans to invest in an R&D project with certain payoff V. The total expenditure $K(t)$ needed to complete the project is uncertain and largely irreversible. The realisation of this project takes time and the completion date T is not known. Furthermore, the firm can reconsider the continuation of the project depending on the progress made by investing (sequential decision problem with the option to abandon). The required time build is captured by a maximum productive investment rate $I_{\max}$ that we assume to be constant[5]. The firm relies on its own financial resources, but a part of the investment cost can be taken over by a governmental R&D subsidy programme[6]. Thus, we replace $I_{\max}$ by $(1-s)I_{\max}$ with s being the investment subsidy rate[7]. We assume $s = 0.5$, which is a typical funding rate for the private sector in national and EU R&D programmes. The timing of subsidies is subject to uncertainty. Two regimes are considered. In the first one, the

[5]Thus, we can directly compare the impact of policy uncertainty with the results obtained in the model considering technical uncertainty exclusively. The relaxation of this assumption would be a topic for future research.

[6]We do not take into account costs occurring in the application process for R&D funds as well as sunk costs in the case that the project is not approved nor costs in the case that the project is abandoned.

[7]As the subsidy relaxes the financial constraints, the speed of investment can be increased. An interpretation is that the firm is able to increase its production capacities.

duration of support via subsidies is not known (policy switch-off at stochastic time T_C). In the second regime, the launch of a new R&D programme is uncertain (policy switch-on at stochastic time T_C). These kinds of policy uncertainties will be modelled with the Weibull distributions $f_{\mathrm{wb}}(T_C)$ specified in Section 4.3.1. Note that the possibility of a policy change is exogenous to the single firm[8].

By investing, the firm reduces the total cost expected for completing the project. But the remaining sum is subject to uncertain changes that are caused by scientific progress or technical drawbacks during the implementation. Like in Chapter 3, the expected change in the remaining cost to completion is modeled by a controlled diffusion process

$$dK(t) = -I(t)dt + \gamma\sqrt{I(t)K(t)}d\omega(t) \ . \tag{4.4}$$

Again, the control $I(t)$ can take two values: $I = I_{\mathrm{max}}$ if it is optimal to invest, and $I = 0$ otherwise. γ measures technical uncertainty, and $d\omega(t)$ is the increment of a Wiener Process.

The firm decides whether or not to invest by comparing expected cash-flows from the project (once it is realised) with the cumulated sum of investments needed. If the benefits are larger than these costs, investment is optimal. Otherwise the project is abandoned. Note that investment costs are irreversible. The value of the investment opportunity is described by the value function $F(K(t))$. Only if $F(K(t)) > 0$, is the R&D project profitable. If $F(K(t))$ equals zero, the firm is indifferent as to whether or not to invest. The assumption of a maximum productive investment rate implies that subsidies only influence $F(K(t))$ by lowering the firm's own investment expenses. Hence, governmental support can induce the firm to invest in R&D projects that would otherwise not be started. This creates two critical thresholds for the total sum of investment. The first one is the value that makes investment optimal due to the subsidy. The second one is the threshold that makes investment optimal regardless of policy support. The value function $F(K(t))$ is given by

$$F(K(t)) = \max_{I(t)} \mathcal{E}_0 \left[\int_T^\infty P\exp(-rt)dt - \int_0^T I(t)(1-S(t))\exp(-rt)dt \right] \ , \tag{4.5}$$

where $\mathcal{E}_0$ is the present expectation value operator, r is the discount rate, and $S(t)$ is the subsidy rate.

In the deterministic case, i.e. if $\gamma = 0$, we can derive an analytical solution for Eq. (4.5) using $T = K/I_{\mathrm{max}}$ and $V = P/r$. For the policy switch-off regime, it holds that $S(t) = 0$ for $t > T_C$ and $S(t) = s$ for $t < T_C$. We obtain

$$K^*(\gamma = 0, T_C) = \frac{I_{\mathrm{max}}}{r} \ln\left(\frac{1 + r\,V/I_{\mathrm{max}}}{1 + s\,(e^{-r\,T_C} - 1)}\right) \ . \tag{4.6}$$

[8]It would be possible to allow e.g. the size of subsidies to depend on the progress of a single R&D project, but this is left to future research. Such an extension would require a stochastic drift term $I(t,v)$ with v describing stochastic policy changes in the controlled diffusion process for the development of critical investment cost K^*, see Eq. (4.4).

For the policy switch-on regime, $S(t) = 0$ for $t < T_C$ and $S(t) = s$ for $t > T_C$, we get

$$K^*(\gamma = 0, T_C) = \frac{I_{\max}}{r} \ln\left(\frac{1 - s + r\,V/I_{\max}}{1 - s\,e^{-r\,T_C}}\right) \quad . \tag{4.7}$$

For $s = 0$, both results are reduced to Eq. (3.8) as expected.

In the uncertainty case, we solve the problem by a backward Monte Carlo simulation using the Longstaff-Schwartz method (Longstaff and Schwartz, 2001)[9]. For varying technical uncertainties γ, we simulate the dependence of the critical investment threshold K^* on T_C. Next, we convolute each of the functions $K^*(\gamma, T_C)$ with the Weibull distributions specified in Section 4.3.1. By this, we obtain a Weibull average for K^* denoted by $< K^* >$. This value is then a function of both technical and policy uncertainty parameters[10]. $< K^* >$ is formally defined as

$$< K^*(\gamma, T_C) >= \int_0^\infty K^*(\gamma, T_C)\, f_{\rm wb}(T_C)\, dT_C \Bigg/ \int_0^\infty f_{\rm wb}(T_C)\, dT_C \quad . \tag{4.8}$$

4.4.2. Discussion of the results

Uncertainty about the duration of R&D subsidies (switch-off regime)

We consider the same set of parameters as used for the basic model in Section 3.3. A firm invests with a maximum productive investment rate of $I_{\max} = 2$ yielding a payoff from the project after completion of $V = 10$. The discount rate is $r = 0.05$. Thus, in the certainty case, K^* can grow from 8.9 ($s = 0$ for all times t) to 16.2 (with $s = 0.5$ for all t). This follows from Eq. (4.6) and creates the two black dashed lines in Fig. 4.5. If subsidies are cut at a certain time T_C, K^* is given according to Eq. (4.6). This result is shown by the black solid line in Fig. 4.5. The other graphs show the critical investment threshold K^* as a function of T_C for different values of the technical uncertainty γ. The lines interpolate the symbols, which themselves show the values obtained by different simulations. As expected from the basic model in Section 3.3, K^* increases with higher γ and the larger T_C. In addition, Fig. 4.5 shows a grey line at $T_C = 3$ years. The grey line shows the expectation value of the Weibull distribution $\mathcal{E}_{WB} = 3$ years. The two dashed lines at $T_C = 1.8$ years and $T_C = 4.2$ years indicate the corresponding confidence interval of the standard deviation $\sigma = \sqrt{\mathcal{V}ar(T_C)}$ (see Eq. (4.3). We will use this interval to show the effect of policy uncertainty.

The convolution of the $K^*(\gamma, T_C)$-functions with the Weibull distributed T_C, Eq. (4.1), yields the blue symbols in Fig. 4.6. For expected investment cost to completion K greater than the values depicted by the symbols, investment is not profitable even with policy support. There is also a region where investment is profitable in the absence of policy support - the region below the black graph which results from assuming $s = 0$ for any time.

[9]Details are described in Section 3.3.2. We approximate expected conditional project values in the simulation using a polynomial regression of degree 5.

[10]This allows us to substantially shorten the simulation time by not having to simulate both uncertainties at once.

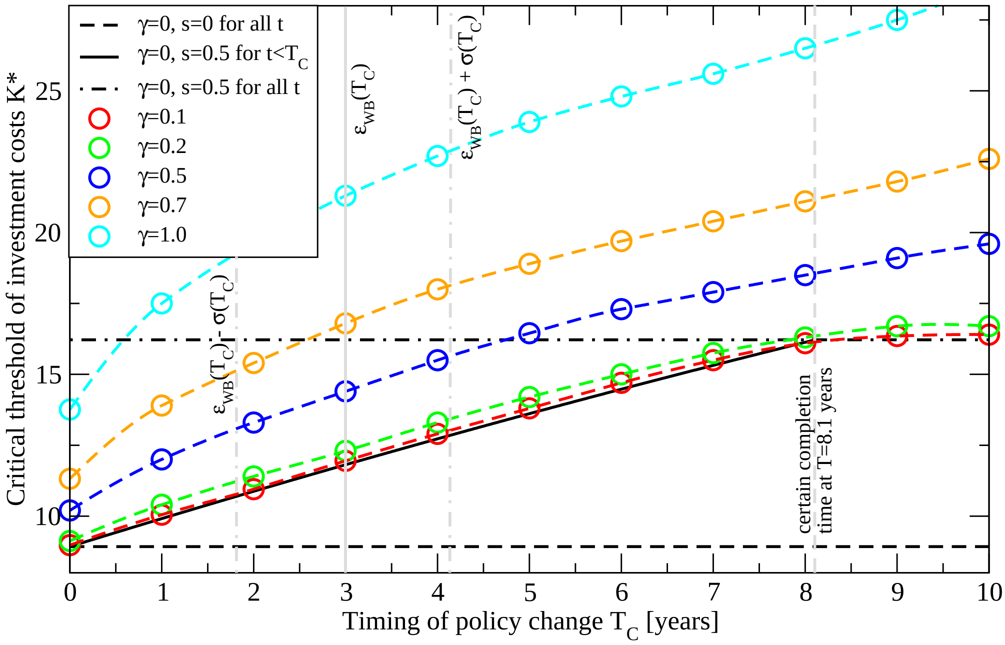


Figure 4.5.: Critical threshold K^* as a function of the time T_C at which subsidies are cut to zero for different values of technical uncertainty γ (policy switch-off regime).

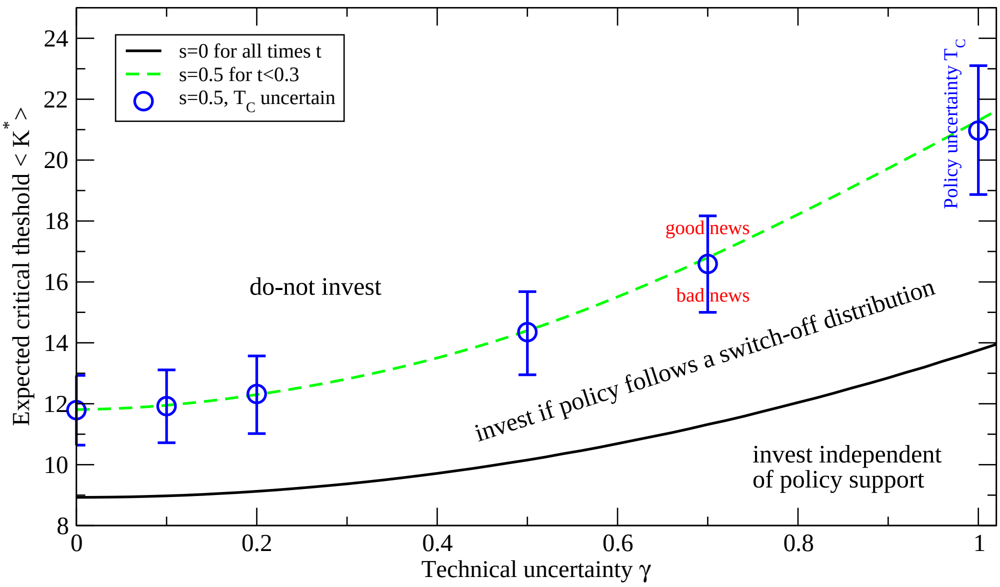


Figure 4.6.: Average critical threshold of investment costs $< K^* >$ as a function of technical uncertainty γ and uncertainty about the time of a policy change T_C.

Fig. 4.6 furthermore shows a dashed green line obtained by assuming a certain change in the policy at $T_C = 3$ years. Note that for higher γ, the blue symbols are slightly below the green line. This is caused by policy uncertainty. The deviation towards smaller K^* for $\gamma > 0$ results from the asymmetry of the Weibull distribution due to our choice of parameters.
The distribution of subsidy cut-offs is almost symmetric with a maximum around 3 years and reaching zero around seven years. The small asymmetry towards the likelihood of a shortened provision of subsidies lowers K^*. In between the black and the green line, investment is profitable if the switch-off time of subsidies is Weibull distributed.

The impact of uncertainty about the duration of policy support can be seen from the error margins σ to the blue symbols.[11] K^* shifts to lower values in case of bad news whereas, good news enlarges the region of profitable investment. For $\gamma = 0$, these values show the exclusive impact of policy uncertainty on K^*. In this case, the critical investment threshold can take values between $K^* = 10.7$ and $K^* = 12.9$.[12] Finally, it can be seen that with growing technical uncertainty γ, the error margins $\sigma(T_C)$ increase. Hence, the optimal investment strategy becomes more sensitive to policy uncertainty the more the R&D project is subject to technical uncertainty.

Uncertainty about the launch of an R&D programme (switch-on regime)

The same parameter set-up is used to study the impact of an uncertain arrival of investment subsidies of size $s = 0.5$. The parameters are $I_{\max} = 2$, $V = 10$, and $r = 0.05$. The expectation of the arrival time is $\mathcal{E}_{WB}(T_C) = 2$ years with standard deviation $\sigma(T_C) = 0.5$ years. The critical costs to complete the project K^* in dependence on technical uncertainty γ and a certain change in policies at T_C are shown in Fig. 4.7. If both uncertainties are absent, we obtain the dashed/dotted black lines and the black solid line. These lines follow from assuming $s = 0$ at any time, $s = 0.5$ for all times, and $s = 0.5$ for $t > T_C$, respectively. For $\gamma > 0$, results are again obtained by Monte Carlo simulations. Fig. 4.7 shows that the later the subsidies are available, the lower K^* is. K^* also decreases with lower γ. Note that a launch of the R&D programme later than $T_C = 4.5$ for $\gamma = 0$ means that the project is never supported. From the convolution of each of the $\gamma - T_C$-functions with the Weibull distribution, Eq. (4.1), we obtain the dependence of $< K^* >$ on both uncertainties. This is illustrated in Fig. 4.8. The result is similar to the switch-off regime. The plane of $< K^* >$ and γ is divided into three regions: a region where investment is also profitable in the absence of policy support, a region where investment is profitable if subsidies are Weibull distributed, and a region where investments are not profitable at all. The latter region expands in case of bad news and shrinks in case of good news about the up-coming policy support. There are three differences in comparison to the switch-off regime. First, in the switch-off regime, the gap between $< K^* >$ in the case of uncertain policy support and the case of no policy support grows with technical uncertainty γ (see Fig. 4.6).

[11] The error margins are obtained by evaluating K^* at $E(T_1) \pm \sigma(T_1)$ in Fig. 4.5 for each γ.

[12] Note that $K^* = 8.9$ if $s = 0.0$ for all times, and $K^* = 16.2$ if $s = 0.5$ for all times. This holds in the absence of uncertainties.

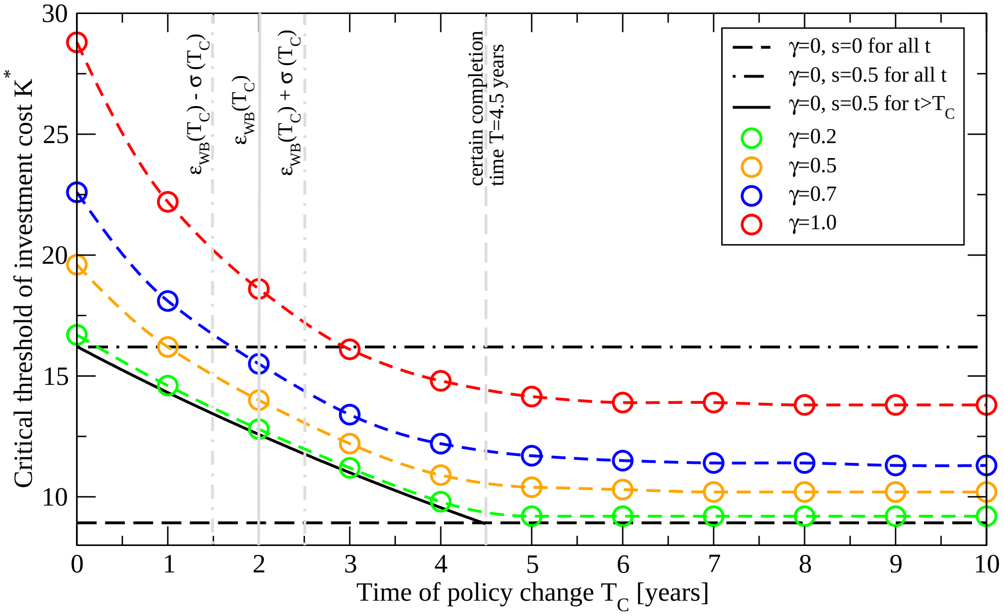


Figure 4.7.: Critical threshold K^* in dependence of the time T_C for launching an R&D programme and technical uncertainty γ (policy switch-on regime).

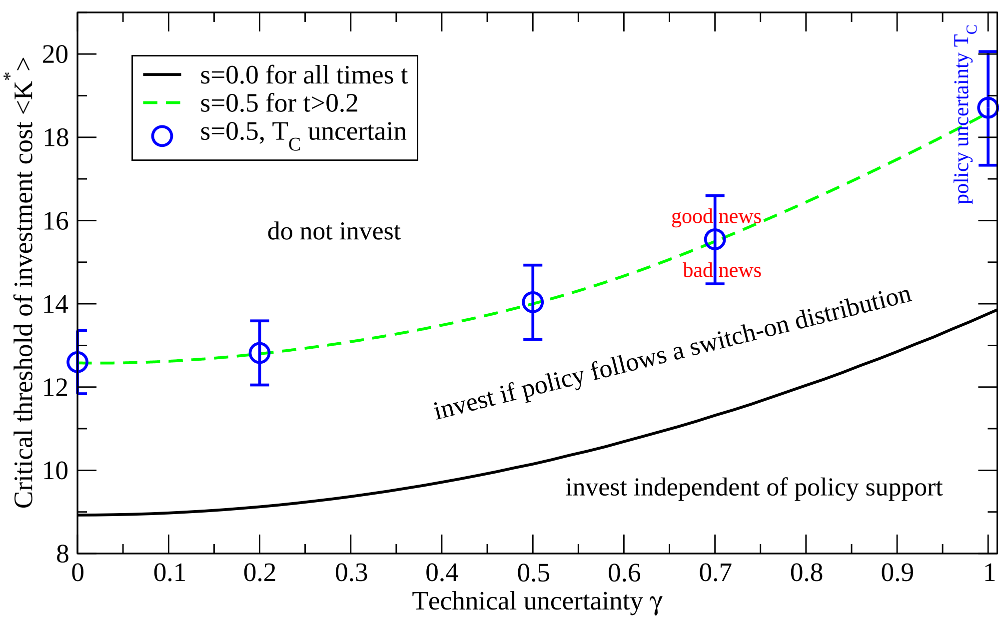


Figure 4.8.: Average critical threshold of investment cost $< K^* >$ as a function of technical uncertainty γ and uncertainty about the time of a policy change T_C.

But in the switch-on regime, the distance between these two regions does not change. Note that $\gamma \geq 0.5$ for typical R&D projects (see Section 3.4.3). Second, $< K^* >$ is more sensitive to policy volatility in the case of the switch-off regime. Both effects imply that certainty about the prospect of continuing a project with policy support is more valuable than certainty about the launch of an R&D programme.

Third, an imaginary line connecting the blue symbols in Fig. 4.8 is slightly higher than the dashed green line. This is opposite to Fig. 4.6. This is caused by our different choices for the parameters of the Weibull distribution. Note that the Weibull distribution in the switch-on regime has an asymmetry towards switching times smaller than the expectation value set to $T_C = 2$ years. While this enlarges the region of profitable investments, the opposite is true for the switch-off regime.

Conclusions and limitations

We have studied the impact of technical uncertainty and uncertainty about the timing of subsidies on R&D investment conditions.[13] Technical uncertainty can be actively reduced by a continuation of investments. The timing of an R&D programme is modelled with a Weibull distribution allowing for time-dependent arrival rates. We find that the critical threshold of investment costs increases with technical uncertainty. Policy uncertainty creates uncertainty about this critical threshold. In case of bad news (i.e. an earlier cut in subsidies or their later introduction), the region of profitable investment shrinks. However, it enlarges if the news about policy support is good. The critical threshold for the cost to completion is more sensitive to an uncertain policy timing for higher values of technical uncertainty γ. This effect is relatively small in the policy regime with an uncertain launch of an R&D programme.

Several simplifications have been made in the model. In addition to the limitations of the basic model discussed in Section 3.3.4., the extended model leaves out costs occurring during the application process for subsidies. Furthermore, we have neglected costs occurring when the project is stopped mid-stream, e.g. a reclaim of subsidies. Finally, policy uncertainty is not related to other model parameters. The relaxation of these assumption is left to future studies.

4.5. Application: uncertain energy taxes and quota

4.5.1. The model and its solution

We extend the model from Section 3.5 by introducing policy uncertainty about the timing of a change in energy taxes and quotas. Again, a firm plans to self-finance an R&D project for developing a more energy-efficient technology. There is a maximum productive rate $I_{\max}$ describing that the project needs time to be completed. The firm has the option to abandon the project mid-stream. We assume a Cobb-Douglas production function with decreasing returns to scale for the inputs of energy and labour. The efficiency in the use of energy is described by technology parameter ϕ.

[13]For comparative statistics of other model parameters, see Section 3.3.3.

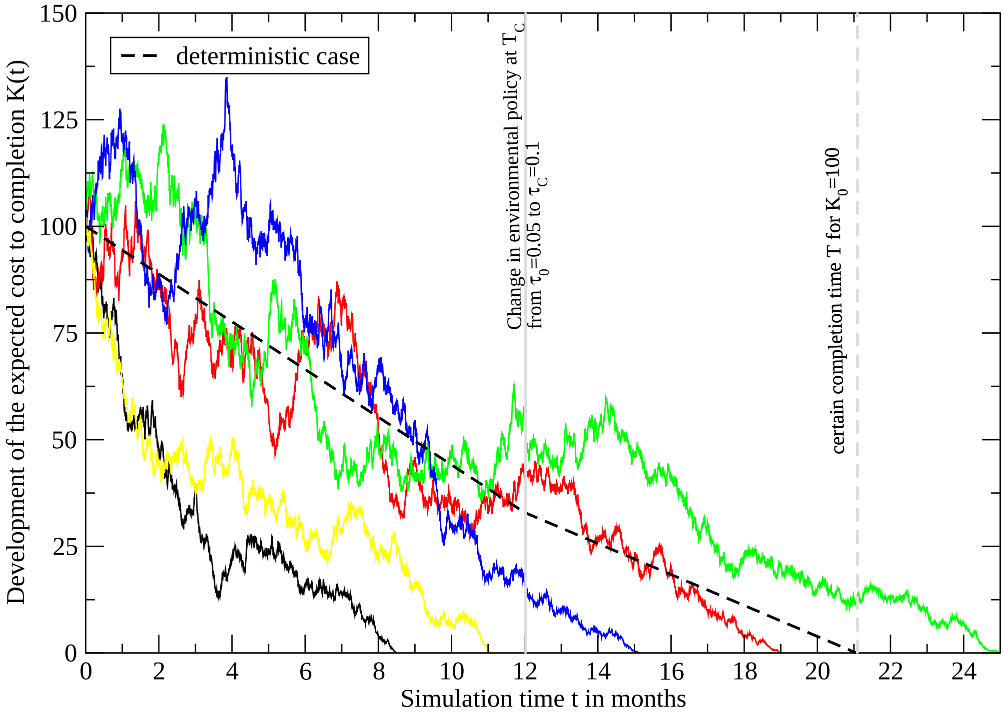


Figure 4.9.: Evolution of expected investment cost under policy change.

The firm makes two decisions. First, it decides about the optimal input of energy and labour, maximising profit flows from production. These in turn determine the resources available for R&D investments. The optimal choice of inputs depends on input and output prices, production elasticities, the environmental policy regime and its timing, as well as the technology parameter. The second decision concerns the optimal investment path. This is a question of whether to continue or abandon the project. The firm compares expected payoffs from the project with the expected sum of investments required for its completion. Technical uncertainty leads to stochastic fluctuations in the development of expected cost to completion. The central parameter is the overall technical uncertainty γ. To highlight the fact that uncertainty is higher in earlier phases of the project, we additionally introduce the parameter δ (Kort, 1998). The evolution of the expected cost to completion $K(t)$ is furthermore dependent on the firm's investment rate, the timing of environmental policy, and the magnitude of its change. The project is realised if $K(T) = 0$. T is the stochastic completion time. This is illustrated in Fig. 4.9, which shows the evolution of initial investment cost of $K_0 = 100$. In the example, the stringency of environmental policy changes at $T_C = 12$ months from $\tau_0 = 0.05$ to $\tau_C = 0.1$. In the certainty case, the project is completed after 21 months assuming costs are being reduced by investing at $I_{\max}$. We use a controlled diffusion process to describe this behaviour (Pindyck, 1993).

Policy uncertainty, i.e. the stochastic timing of a policy change at T_C, is given by the Weibull distribution specified in Section 4.3.2. As in Section 3.5.2, we consider two environmental-policy regimes: a tax regime setting a per-unit energy tax τ, and a quota regime with a binding quota on the use of energy $\bar{E}$ (van Soest, 2005). The government chooses the tax rate equalising marginal benefits and costs of the firm. The amount of energy chosen by the firm in this case also defines the energy quota.

To solve the sequential investment problem, we first derive a solution for the problem considering only technical uncertainty dependent on a certain change in policies. For this, Eqs. (4.9, 4.11-4.17) have to be solved (see the next page). Tab. 4.1 provides the description of all variables.

1. Technical and policy uncertainty, policy equations

$$\begin{aligned} dK(t) &= -I(t)dt + \gamma(K(t))^{\delta}\sqrt{I(t)K(t)}d\omega(t) \ , && (4.9) \\ f_{wb}(T_C) &= a\, b\, T_C^{b-1}\exp(-aT_C^b) \ , && (4.10) \\ \bar{E}(\tau,\phi_0) &= \left[P\theta\left(\frac{\beta}{w}\right)^{\beta}\left(\frac{\alpha}{z+\tau}\right)^{1-\beta}\right]^{\frac{1}{1-\alpha-\beta}}\phi_0^{\alpha/1-\alpha-\beta} \ . && (4.11) \end{aligned}$$

2. Optimal choice of inputs by the firm

$$\begin{aligned} q(E,L) &= \theta(\phi_1 E)^{\alpha}L^{\beta} \text{ with } \alpha,\beta>0,\ \ \alpha+\beta<1 \ , && (4.12) \\ \pi^k(\phi(t),\tau(t)) &= \begin{cases} \xi^{\mathcal{T}}\phi_1^{\alpha/(1-\alpha-\beta)} & \text{for } \ k=\mathcal{T} \ , \\ \xi^{\mathcal{Q}}\phi_1^{\alpha/(1-\beta)} - z\bar{E} & \text{for } \ k=\mathcal{Q} \ , \end{cases} && (4.13) \\ \xi^{\mathcal{T}} &= [1-\alpha-\beta]\left[P\theta\left(\frac{\alpha}{z+\tau}\right)^{\alpha}\left(\frac{\beta}{w}\right)^{\beta}\right]^{1/(1-\alpha-\beta)} \ , \\ \xi^{\mathcal{Q}} &= (1-\beta)\left[P\theta\bar{E}^{\alpha}\left(\frac{\beta}{w}\right)^{\beta}\right]^{\frac{1}{1-\beta}} \ . && (4.14) \end{aligned}$$

3. Optimal R&D investment decision by the firm
3a. Policy changes before the R&D project is completed, i.e. $T_C < T$

$$\begin{aligned} F^k(K(t)) = \max_{I(t)}\mathcal{E}_0 \Bigg[&\int_T^{\infty}\pi^k(\phi_1,\tau_C)\exp(-rt)dt \\ &- \int_0^{T_C}\pi^k(\phi_0,\tau_0)\exp(-rt)dt - \int_{T_C}^{T}\pi^k(\phi_0,\tau_C)\exp(-rt)dt\Bigg] \ . \qquad (4.15) \end{aligned}$$

3b. Policy changes after the R&D project is completed, i.e. $T_C > T$

$$\begin{aligned} F^k(K(t)) = \max_{I(t)}\mathcal{E}_0 \Bigg[&\int_T^{T+T_C}\pi^k(\phi_1,\tau_0)exp(-rt)dt + \int_{T+T_C}^{\infty}\pi^k(\phi_1,\tau_C)\exp(-rt)dt \\ &- \int_0^{T}\pi^k(\phi_0,\tau_0)\exp(-rt)dt\Bigg] \ . \qquad (4.16) \end{aligned}$$

3c. Self-financing restriction

$$I(t) = \begin{cases} I^k_{\max} = \pi^k(\phi(t),\tau(t)) & \text{if } \ F(K(t))>0 \ , \\ I^k_{\max} = 0 & \text{else } \ . \end{cases} \qquad (4.17)$$

1. Technical and policy uncertainty

Eq. (4.9)	$K(t)$ - expected investment cost to completion
	$I(t)$ - rate of investment
	t - time
	γ - technical uncertainty, parameter > 0
	δ - technical uncertainty, parameter $0 < \delta < 0.5$
	$d\omega(t)$ - increment of Wiener process
Eq. (4.10)	f_{wb} - Weibull distribution
	T_C - time of policy change
	a - scale parameter > 0
	b - shape parameter > 0
Eq. (4.11)	$\bar{E}(\tau, \phi_0)$ - energy quota (see also A.5.1. for the derivation)
	$\tau(t)$ - per-unit energy tax rate
	ϕ_0 - current technology for the use of energy
	P, w, z - price of output, labour, and energy
	α, β - production elasticities of energy and labour
	θ - general productivity parameter

2. Optimal choice of inputs by the firm

Eq. (4.12)	q - Cobb-Douglas production function for output $q(E, L)$
	E, L - inputs of energy and labour
	ϕ_1 - improved energy technology after completion of R&D project
Eq. (4.13),	$\pi^k(\phi(t), \tau(t))$ instantaneous profit flows of the firm, see also A.5.1.
Eq. (4.14)	k - denotes the policy regime: taxes or quotas
	$\phi(t)$ - available technology for the use of energy
	$\tau(t)$ - environmental stringency, subject to uncertain timing T_C

3. Optimal R&D investment decision of the firm

Eq. (4.15),	$F(K(t))$ - value of investment opportunity
Eq. (4.16)	ϕ_1 - technology after completion of R&D project
	ϕ_0 - technology before completion of R&D project
	T - completion time of R&D project
	T_C - uncertain time of policy change relative to T
	τ_0 - environmental stringency before policy change
	τ_C - environmental stringency after policy change
	r - discount factor
Eq. (4.17)	$I^k_{\max}$ - maximum productive investment rate

Table 4.1.: Set of variables and parameters.

Parameter	Value
Technical uncertainty γ	0 .. 1.0
Technical uncertainty δ	0,0.1
Energy output elasticity α	0.3
Labour output elasticity β	0.5
Total factor productivity θ	1.0
Output price P	1.0
Input price of energy z	0.1
Input price of labour w	0.2
Energy efficiency of current technology ϕ_0	1.0
Energy efficiency of future technology ϕ_1	1.5
Discount rate r	0.05
Time of policy change T_C	0 .. 50
Per-energy tax rate τ	0 .. 1.0
Number of paths	10000
Number of time steps	30000
Degree of polynomial fit	5
Simulation time	50 (months)

Table 4.2.: Parameters used in the numerical solution.

Eqs. (4.9, 4.11-4.17) are solved for both policy regimes using a Monte Carlo simulation. The basic procedure for the simulation has been discussed in Section 3.3.2, but in order to incorporate a change in policies, the simulation has to be extended. It needs to be tested whether policies change before or after the completion of the R&D project since available investment resources and payoffs from the project depend on the policy parameter τ. The solution of this problem is described by a critical threshold $K^*(t;\gamma,\delta,T_C,\tau)$.[14] If the expected investment costs to completion $K(t)$ are larger than this value, investment is not profitable. K^* is a function of the model parameters (see Tab. 4.2). We will focus on the impact of technical and policy uncertainty.[15]

The results from the first step of the solution procedure are shown in Fig. 4.10. The blue (red) symbols are the simulation results for the quota (tax) regime. The dashed lines are interpolations of these results.

Next, we convolute the functions $K^*(\gamma,T_C)$ with the Weibull distribution for T_C, Eq. (4.10). Doing so, we obtain the Weibull weighted average of K^* denoted by $< K^* >$. This value is a function of both uncertainties. Formally, this means

$$< K^*(\gamma,T_C) >= \int_0^\infty K^*(\gamma,T_C)\, f_{\mathrm{wb}}(T_C)\, dT_C \Big/ \int_0^\infty f_{\mathrm{wb}}(T_C)\, dT_C \; . \qquad (4.18)$$

Fig. 4.11 shows the result for $< K^*(\gamma,T_C) >$. Parameter choices for technical uncertainty

[14] Following, we will use the short notation $K^*(\gamma,T_C)$.
[15] See Section 3.5 for the comparative statistics of the other parameters.

are $\gamma = \delta = 0$, or $\gamma = 0.5$ and $\delta = 0.1$. Parameter choices for policy uncertainty are $\mathcal{E}(T_C) = 12$ months or $\mathcal{E}(T_C) = 24$ months. For the case that a policy change is expected within 1 year, we calculate the results for two Weibull distributions with one having constant and the other time-dependent arrival rates (see Fig. 4.4).

In the deterministic case ($\gamma = 0$, T_C certain), the critical investment threshold K^* can be derived analytically. A change in the level of environmental stringency from τ_0 to τ_C at T_C before and after the R&D project is completed at T yields the result

$$
\begin{aligned}
&T_C < T: \qquad\qquad\qquad\qquad\qquad\qquad\qquad\qquad\qquad\qquad\qquad\qquad\qquad\qquad (4.19)\\
&\quad K^* = \frac{I^k_{\text{max}}(\tau_C,\phi_0)}{r} \ln\left(\frac{1 + r\,V^k(\tau_C,\phi_1)/I^k_{\text{max}}(\tau_C,\phi_0)}{e^{-rT_C} + (1 - e^{-r\,T_C})\,I^k_{\text{max}}(\tau_0,\phi_0)/I^k_{\text{max}}(\tau_C,\phi_0)}\right)\\
&\qquad\quad + T_C(I^k_{\text{max}}(\tau_0,\phi_0) - I^k_{\text{max}}(\tau_C,\phi_0)) \ ,\\
&T_C > T:\\
&\quad K^* = \frac{I^k_{\text{max}}(\tau_0,\phi_0)}{r} \ln\left(\frac{1 + r\,V^k(\tau_0,\phi_1)/I^k_{\text{max}}(\tau_0,\phi_0)}{1 + r(V^k(\tau_0,\phi_1) - V^k(\tau_C,\phi_1))/I^k_{\text{max}}(\tau_0,\phi_0)\,e^{-r\,T_C}}\right) \ .
\end{aligned}
$$

$V^k = \pi^k/r$ is the payoff after completion. Other variables are given in Tab. 4.1. The dependence on energy efficiency parameters ϕ_0 and ϕ_1 leads to different certain completion times T, which are $T = 14.8$ months in case $T_C = 12$ months and $T = 15.7$ months in case $T_C = 24$ months (quota regime). For the tax regime, we get $T = 16.5$ months in case $T_C = 12$ months and $T = 17.3$ months in case $T_C = 24$ months. Functions $K^*(T_C)$ given by Eqs. (4.19) for both policy regimes are illustrated in Fig. 4.10. The solid red line (case $T_C < T$) and the dotted red line (case $T_C > T$) are the calculations for the tax regime. The solid blue line (case $T_C < T$) and the dotted blue line (case $T_C > T$) are the calculations for the quota regime.

4.5.2. Discussion of the results

Fig. 4.10 shows the critical cost to completion K^* as a function of the time of a certain policy change T_C using different technical uncertainties γ. Blue (red) symbols are simulation results for quotas (taxes). The dashed lines interpolate these symbols. We find for both policy regimes that K^* increases the later the environmental policy switches to a stricter level. An increasing energy quota or energy tax reduces investment resources as well as cash-flows from the project after its completion. The region where investment is profitable expands when γ grows. The quota regime yields larger K^* compared to the tax regime. The latter findings confirm the results of the model in Section 3.5. There, environmental policy was set once and for all. For $\gamma = 0$, the inflexion point is reached when the policy changes exactly at the completion time of the project. This is where the solid and the dotted line meet.

The introduction of uncertainty over the timing of an environmental policy change has an ambiguous effect on the borderline between the profitable and unprofitable investment regions. The ambiguity can be related to the existence of an inflexion point at which the curve changes from a concave to a convex slope. If the policy is expected to change within the investment phase, we are to the left of the inflexion point, and hence the convolution

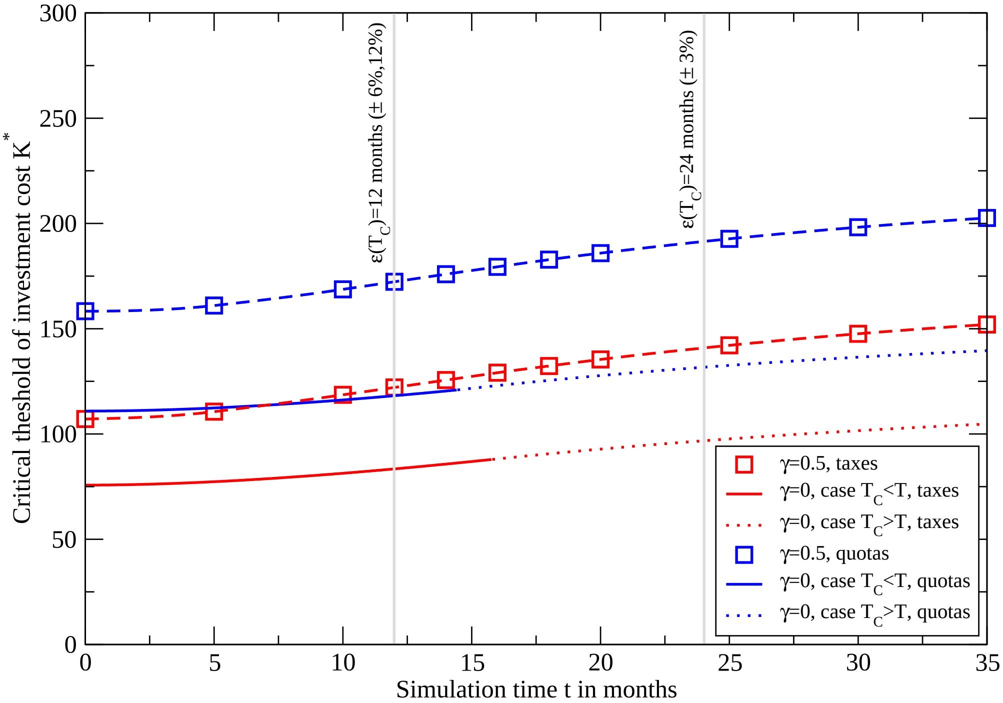


Figure 4.10.: Critical investment cost K^* as a function of the time of a policy change T_C and technical uncertainty γ.

will lead to a slight increase, in the case that the Weibull distribution is similar to a Gaussian distribution. But if the policy is expected to change after the project's completion, we are to the right of the inflexion point and the slope is convex. Therefore, the convolution with a Weibull distribution, similar to a Gaussian distribution, will decrease the critical threshold of investment, K^*. Finally, assuming time-independent arrival rates for the policy change, K^* will decrease in all cases.

With the introduction of policy uncertainty we find generally that its impact is of much smaller magnitude in comparison to the influence of technical uncertainty. Fig. 4.11 visualises the results in a certainty-uncertainty plane for the dependence of critical investment cost K^* on the two policy regimes. In the deterministic case (upper left part), the expected investment cost to completion can increase up to 83.4/118.2 (tax regime/quota regime) if the environmental policy is changed in month 12. In the case that the policy change happens after the completion of the project in month 24, the deterministic K^* can increase up to 96.8/131.7 (taxes/quotas).

Next, we consider policy uncertainty while keeping $\gamma = 0$ (see lower left part of 4.11). We observe a slight improvement of the investment conditions in case a policy change is expected in a year and in case arrival rates are time-dependent. The corresponding Weibull distribution has a small asymmetry towards later policy changes, and furthermore we are to the left of the inflexion point (compare 83.4 with 83.6). However, assuming a constant arrival rate for the switch in policies and fitting the same expectation value

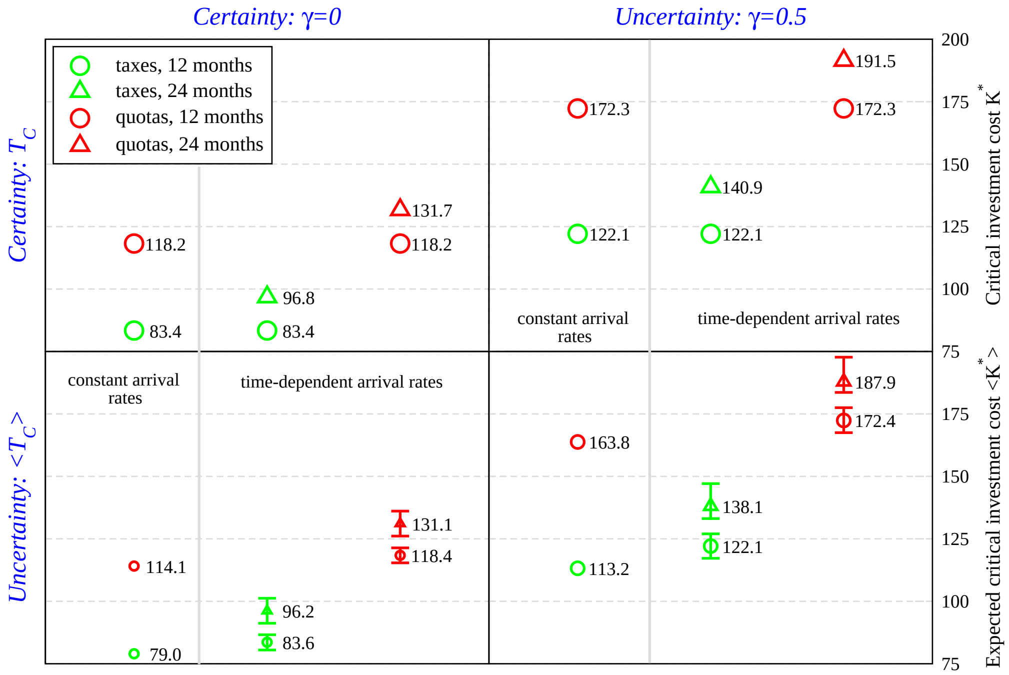


Figure 4.11.: Critical investment cost K^* for quotas and taxes in dependence of technical and policy uncertainty, γ and T_C.

for T_C, $< K^* >$ decreases to 79.0/114.1 (taxes/quotas). $< K^* >$ is also lowered if the policy change is expected in month 24. In this case, the firm is very likely to complete the project before the change in policy takes place, i.e. we are to the right of the inflexion point. Error bars for $< K^* >$ are symmetric. The impact of positive (negative) surprises from the government enlarge (shrink) the region of profitable investment with the same magnitudes.

The upper right part of Fig. 4.11 shows the effect on K^* when only technical uncertainty is present. We observe that the critical threshold for investment cost strongly increases for both policy regimes and for policy switching times. Considering in addition policy uncertainty, $< K^* >$ decreases in all cases (lower right part of Fig. 4.11). Hence, if technical uncertainty is present, the effect of policy uncertainty is not ambiguous. The reduction of $< K^* >$ is strongest when assuming constant arrival rates for a change in policies. We furthermore find that the inclusion of both policy and technical uncertainty leads to an asymmetric impact on the standard deviation $\sigma(T_C)$ (depicted by error bars) of $< K^* >$. This effect is particularly large for the quota regime.

We can summarise the following. First, taking account of technical and policy uncertainty, conditions for environmental R&D investments are considerably affected compared to the case of certainty, but technical uncertainty has a much stronger impact. This is not at odds with Pindyck's findings (see e.g. Pindyck (1993)). I consider an uncertainty about the timing of a policy change, whereas Pindyck assumes that cost uncertainty affects the project throughout its lifetime. Secondly, the effect of policy uncertainty can be ambiguous depending on the specification for the distribution and the slope of K^*. These results are in line with the literature (Hassett and Metcalf, 1999; Böhm and Funke, 2000, e.g.). In most cases, we find that the critical threshold for the cost to completion decreases when both types of uncertainties are considered. However, if policy changes are expected in the more distant future, policy uncertainty can enlarge the region where investment is profitable. Good surprises about environmental policies have a stronger impact on the critical threshold than negative surprises.

We have made several assumptions. First, the limitations of the basic model continue to apply. These have already been discussed in Section 3.5.6. In addition, we have assumed that the timing of policies and the magnitude of change are exogenous to the model. A coupling of both parameters with e.g. the evolution of the expected cost to completion or an objective function of a social planner is an interesting topic for future research. This furthermore raises the issue of time-inconsistency of environmental policy and strategic behaviour of firms undertaking the R&D. Another interesting aspect to explore is the effect of uncertainty of the magnitude of a policy change.

4.6. Chapter summary

We have extended the models with technical uncertainty discussed in Chapter 3 by including uncertainty about the timing of technology and environmental policy. The stochastic description is modelled by Weibull distributions allowing for time-dependent arrival rates. We match these distributions to mimic current expectations about the timing of governmental R&D programmes.

First we modelled uncertainty about the availability of investment subsidies in two different scenarios. In the first scenario, the firm undertaking R&D is uncertain about the continuation of governmental support: the R&D programme is already in place. In the second scenario, we studied an uncertain start of a new R&D programme mimicking current expectations about the upcoming German Energy Research Programme. For both scenarios, we obtain that policy uncertainty increases the volatility of the critical threshold for the cost to complete the project. This effect is amplified the more the project is subject to technical uncertainty. The effect is stronger for the first scenario.

The second model type examined the influence of an uncertain timing in a change in environmental regulation. We studied how this impacts the decision to invest in R&D of an energy-saving technology. Expectations about an increase in the stringency of policies are designed to resemble a possible upcoming jump in taxes for the use of electricity in Germany. Considering energy taxes and quotas, we found, similar to the results in Chapter 3, that the latter are preferable for our choice of model parameters. The critical threshold for the cost to completion is larger under the quota regime. However, policy uncertainty lowers this critical threshold in most cases. We furthermore observed that the assumption of constant arrival rates for the policy change decreases the critical threshold for the cost to completion. Thus, models allowing for time-dependent arrival rates should predict more optimistic investment conditions.

Common to all models is that the impact of policy uncertainty is smaller than that of technical uncertainty. Despite the limitations imposed, we can conclude that it is more important to incorporate technical uncertainty into investment decision models. However, we have neglected questions of time-inconsistency of environmental policy as well as a strategic behaviour of a firm or a social planner. The sign of the effect of policy uncertainty under these circumstances is, however, of continuing interest.

5. Summary, conclusions, and outlook

The central question of these thesis is: How is the irreversible decision of a firm to invest in environmental R&D influenced by uncertainty about the scientific progress and uncertainty about the regulative environmental policy framework?

We explore sequential investment models that incorporate sunk R&D expenditure, technical uncertainty, and policy uncertainty. Technical uncertainty affects the sum of expected costs to the completion of a research project whose evolution is described by a controlled diffusion process. The stochastic behaviour of policy changes are modelled with a Weibull distribution allowing for time-dependent arrival rates.

The real options models with technical uncertainty and their results are

- Model 1 is a basic sequential investment model that originates from Pindyck (1993). We demonstrate how to solve the model using dynamic programming and Monte Carlo simulations. Comparative statistics and the discussion of model limitations provide the background for further analysis.
- Model 2 is an application to investments into cutting-edge technologies (renewable energy sources). We analyse the investment framework for the case of the first German commercial offshore wind park Baltic 1 in the context of the current Renewable Energy Resources Act. An empirical estimate yields the results that technical uncertainty is of magnitude 0.5 and expected investment cost for Baltic 1 add up to 134-139 MEUR depending on the distance from shore. Our model demonstrates that an investment in a wind park of comparable size is only profitable if the planned sprinter bonus (available for offshore farms in operation before January 2016) is granted along with the foreseen feed-in tariffs for the generation of electricity. Under this policy regime, the risk of abandoning the project is not higher than 9 %.
- Model 3 studies policy incentives, i.e. R&D subsidies, taxes, non-tradable quotas, and emission trading, to encourage invests in R&D of energy-saving technologies. We find that the framework for investments becomes more attractive with increasing technical uncertainty, but it worsens the more stringent environmental policies are set. The firm can actively reduce technical uncertainty by learning and has therefore an interest to continue with investments. Environmental policy, on the other hand, lowers investment resources and prospective payoffs from the R&D project. Among energy taxes, energy quotas, and emission trading, the latter performs best in terms of inducing energy-saving R&D. Against the conventional wisdom, non-tradable quotas are preferable over taxes for realistic policy parameters.

We furthermore find that investment grants are able to compensate for investment conditions worsened under environmental policy regimes mentioned above.

Now we turn to models that include both, technical and policy uncertainty. The models and their results are

- Model 1 studies the effect of uncertainty about the availability of R&D subsidies on the optimal investment decision of a single firm. We consider two scenarios in which policy uncertainty is designed to describe current expectations about EU and national R&D programmes. In the first, the firm undertaking R&D is uncertain about the continuation of policy support. In the second scenario, we analyse an uncertain start of a new R&D programme that provides investment grants. The central finding is that policy uncertainty increases the volatility of the threshold of critical investment costs. The effect is amplified the more the project is characterised by technical uncertainty.
- Model 2 includes uncertainty about the timing of stricter environmental regulation. We analyse the influence of energy taxes and non-binding quotas for energy use on the decision to invest in the development of an energy-saving technology. Expectations about a change in environmental policies are designed to resemble a possible up-coming jump in taxes for the use of electricity in Germany. Model results confirm the preference of the quota regime for our choice of parameters. Unlike technical uncertainty, policy uncertainty lowers the critical threshold for the expected cost to completion in most cases. We furthermore find that the choice of a particular distribution to describe regulative uncertainty matters for the observed effect in terms of its magnitude and direction.
- Common to the models that combine technical and policy uncertainty is that technical uncertainty has a larger influence on the conditions of R&D investments.

Based on the results of the models above, we can conclude that it is indispensable to take into account irreversibility, technical uncertainty, and policy uncertainty. Realistic magnitudes of both uncertainties change the size and direction of parameters that are used to derive optimal R&D investment strategies.

Ideas for future research

Still, our results derive from models that are based on restrictive assumptions. This opens up possibilities for future research including a) an empirical foundation of assumptions or their rejection, and b) a relaxation of the assumptions in extended theoretical models. In particular, we see potential for the following research questions:

1. **Empirical estimation of the real option value and the magnitude of uncertainties in environmental R&D projects**: By considering solely uncertainty about the scientific progress and the policy framework, we distance from

uncertainties in the markets and at an industry-wide level. According to theoretical models, the latter are likely to create an incentive to postpone investments, following from the fact that the majority of firms are price-takers. Price volatilities are hence not influenceable and produce uncertainty about the value of the investment opportunity. However, up to now, only a few empirical tests of the investment-uncertainty relationship are available. Furthermore, we only found one contribution that specifically considers eco-innovations (i.e. their diffusion) in an empirical real options framework (Kumbaroglu et al., 2008). A methodological starting point for such an investigation at firm or project level would be e.g. Bulan (2005), Bloom et al. (2007), Czarnitzki and Toole (2008), Baum et al. (2008), and Johnstone and Hascic (2009). Related to environmental policy and uncertainty are Johnstone et al. (2010), who consider the importance of policy predictability, and Horbach (2008), who estimates the role of an expected future demand for an environmental innovation. A real options model for the diffusion of new renewable power generation technologies is worked out by Kumbaroglu et al. (2008). Finally, uncertainty connected with technical progress of an R&D project is likely to be technology-specific and empirical estimates are therefore of interest.

2. **Imperfect capital markets**: By assuming that a risk-neutral firm owns enough resources to self-finance an R&D project, we neglect financing constraints that in particular small-size firms and newly established companies are likely to be confronted with. There are some contributions that can serve as an entry into this line of research. For example, Kasahara (2008) introduces financing constraints into an optimal investment timing model and studies asymmetric information between risk-neutral lenders and firms. Boyle and Guthrie (2003) also analyse the impact of costly external financing and the possibility of future funding lacks.

3. **Strategic effects and market power**: In analysing the optimal investment strategy of a single firm, we ignore the influence of rivals and market power as well as the possibility of policy anticipation. This opens the door to a game theoretic analysis of the strategic behaviour of competitors and/or the government. Games between rivals as well as models considering positive knowledge spillovers typically deduce an incentive to accelerate investments as each of the firms aims to realise a first-mover advantage and to strengthen its market power (e.g. Kulatilaka and Perotti (1998); Lukach et al. (2007); Ohyama and Tsujimura (2008)). The timing and commitment of environmental policies can be studied in regulation games (see Requate (2005)). For the stage of invention and after the start of an R&D programme, policy adjustments are likely to happen after observing the progress of an R&D project or after recognising industry-wide learning curves. Policies change in dependence on the diffusion rates for the supported environmental technologies. The anticipation of policy changes can in turn lead to a correction of the optimal investment path for a firm undertaking R&D.

4. **Correlation of uncertainties with other model parameters**: In our models, the timing of policy is exogenous. Such a simplification cannot describe the

influence of changing policies that adjust e.g. according to the scientific progress achieved or in dependence on profits realised by firms. An example is the current discussion in Germany about long-term subsidies granted to the solar industry. Therefore, a straightforward extension of our model would be to allow for an uncertain size of the policy change. Another idea would be to couple environmental policy adjustments with model parameters. For example, Hassett and Metcalf (1999) design a model for general capital investments in which the likelihood of policy responses is also triggered by the firm's profitability. Pawlina and Kort (2005) link structural changes in the investment framework to the overall economic performance. The probability of cutting a tax-credit in booming phases is high. Another possibility better suited to R&D investments would be to link learning - i.e. the resolution of technical uncertainty - to policy parameters and/or the industry-wide learning curve.

5. **Linkage to climate modelling**: In our models, we give answers on the optimality of investment decisions from the perspective of a single firm under the influence of policy parameters. However, magnitudes of these parameters do not follow from the objective function of a social planner. In order to derive conclusions about the optimal design of policies from the perspective of a social planner and the difference in implications for the firm's optimal investment framework, our models could be linked to aggregate simulation models. A prospective choice would be climate models, described e.g. in Baker et al. (2007); Bosetti and Tavoni (2009); Golub and Markandya (2009).

This thesis has shed light on the question of how irreversibility and uncertainty affect the optimality of environmental R&D investment decisions. Of course, this is only a piece of the complex puzzle of green technological change and its role in alleviating climate change. Indeed, the puzzle itself is of infinite size. To see the whole picture, it would not only be necessary to take into account all of history but also to anticipate future developments to their full extent. This brings us back to the beginning of this thesis. As it is not possible to fully recover the past, it will not be possible for historians to uncover all details about the nemesis of Ozymandias' kingdom, nor will it be possible to exactly recreate the king's broken statue in the desert. In the same way, economic research will not be able to draw a precise path into the future. But, an interesting point has been made by the author Antoine de Saint-Exupéry in his novel 'The wisdom of the sands'. In this book, the main character, a prince, takes long strolls into the desert with his father talking about the responsibility of decision-makers. On one such stroll, the prince says, 'It is always about arranging the present. What use is it to quarrel over its heritage? The task is not to foresee the future but to enable it.' In this sense, we hope to have contributed to a better understanding about why decisions can be suboptimal and what lessons can be drawn to avoid making them again. There is a value of keeping options open - as states the central paradigm of real options theory.

A. Appendix: Data tables, figures, and calculations

Contents

A.1. Basic background for stochastic processes

- A **Stochastic process** is a time-dependent random variable $X(t)$ whose realisation is a path $x(t)$. It is well defined in a probability space.

- All processes used in this work belong to the class of **Markov processes**. This class of stochastic processes is continuous. A fundamental property of Markov processes is that future developments can be separated from the past ones conditional on the stage when the separation is made. The consequence is that the probability distribution of X_{t+1} can be described by X_t, and a decisions variable a_t, i.e. Lagrangian $L(X_{t+1}|X_t, a_t, t)$.

- **Diffusion processes** belong to the class of Markov processes. They possess the (strong) Markov property. Their sample paths $x(t)$ are almost always continuous functions of t. This means it is relatively unlikely that large displacements occur in ϵ-small time intervals.

- A **Wiener Process** has the Markov equality. Its increments are independent from each other and its infinitesimal time evolution is normally distributed. $dw = \zeta_t \sqrt{dt}$ with ζ_t being a random normally distributed variable.

- An **Ito-Process or Generalized Brownian Motion** also possesses the Markov equality. Such processes are defined as

$$dX = a(X,t)dt + b(X,t)dw \quad . \tag{A.1}$$

  $a(X,t)$ is called the drift rate and $b(X,t)$ is the variance rate. dw is the increment of a Wiener process $w(t)$. It holds that $\mathcal{E}(dw) = 0$, thus $\mathcal{E}(dX) = a(X,t)dt$. The variance of dX is $\mathcal{V}ar[X] = b^2(X,t)dt + o(dt)$.

- **Ito-calculus for stochastic differential equations**. State variable $X(t)$ evolves stochastically over time t. Thus, an ordinary derivative does not exist. The Ito-calculus provides means to work with stochastic Ito-Processes. An approximation for the time derivative using Taylor-expansions is given by

$$dF = \left[\frac{\partial F}{\partial t} + a(X,t)\frac{\partial F}{\partial X} + \frac{1}{2}b^2(X,t)\frac{\partial^2 F}{\partial X^2}\right] dt + b(X,t)\frac{\partial F}{\partial X}dz \tag{A.2}$$

For precise mathematical definitions, see e.g. the monographs of Karlin and Taylor (1981).

A.2. Literature on uncertainty and green technological progress

This section provides summarising tables of the theoretical literature on green technological progress, uncertainty, and environmental policy. Publications are described by four criteria: 1) the type(s) of uncertainties, 2) the kind of irreversibility, 3) the type of the decision-maker (social planner, sector perspective, single firm), and 4) the type of the model (two-period model, time-continuous model, global climate change model, stochastic control model, real options optimal timing model, sequential investment model). The first table includes contributions that analyse the choice of environmental policy instruments. The second table summarises findings with respect to the intensity of environmental policy. The third table comprises the literature on the timing of policies. The fourth table gives an overview on the impact of policy uncertainty. The last two tables present contributions considering uncertainty of green technological progress.

Source	Type of uncertainty	Irreversibility feature	Decision-maker and model	Main finding
Weitzman (1974)	production cost and benefit	-	social planner, two-period model	no first-best solution, ranking of quantity and price instruments depends on relative slopes
Stavins (1996)	Weitzman (1974) correlated	-	social planner, two-period model	covariance can change ranking, with realistic parameters quantity instruments better
Pizer (1999)	economic, climate change	-	social planner, stochastic growth model	uncertainty raises optimal abatement and welfare gains, taxes preferred over control instruments
Newell and Pizer (2003)	production cost and benefit	-	time-continuous Weitzman (1974)	Weitzman's result also holds in the dynamic model, under time-covariance quantities are preferable
Zhao (2003)	abatement cost	investment	social planner, expectation general equilibrium model	cost uncertainty slows down investment, tradable permits preferable over emission taxes
van Soest (2005)	technological progress	investment	single firm, optimal timing RO	earlier adoption under quota for the use of energy if policy is less strict

Table I: Choice of policy instrument under uncertainty

Table A.1.: Theoretical literature on uncertainty and green technological progress, Tables I-VI

Source	Type of uncertainty	Irreversibility feature	Decision-maker and model	Main finding
Kolstad (1996)	damage by global warming	damages, policy	social planner, stochastic economy-climate model	if learning is fast low policy levels are preferable or temporary carbon taxes instead of permanent ones
Ulph and Ulph (1997)	damage cost	stock of GHG	social planner, two-period global warming model	irreversibility is a function of learning impacting global warming models only if uncertainty is high and discount rates are low
Fisher and Narain (2003)	evolution of GHG stock	sunk cost, stock of GHG	social planner, two-period global warming model (DICE)	if risk is endogenous investment is accelerated, irreversibility of investment is larger than that of global warming
Baker et al. (2006)	climate change impact	-	social planner, decision-theoretic model + DICE	optimal R&D can increase or decrease with uncertainty depending on a specific programme, policy can shift the probability of masses
Wirl (2006)	temperature	emissions and their stopping	social planner, optimal timing RO	the optimal irreversible emission strategy is more conservative
Golub et al. (2009)	climate feedback, climate sensitivity, related costs	mitigation costs	social planner, global simulation model (IPCC)	mitigation costs are larger than the benefits from avoided damages but stricter target has higher risks

Table II: Intensity of policy instrument under uncertainty

Source	Type of uncertainty	Irreversibility feature	Decision-maker and model	Main finding
Arrow and Fisher (1974)	development and preservation cost	construction	social planner, two-period model	value to wait with investments, the prospect of resolving uncertainty favours flexibility
Pindyck (2002)	damage cost and benefits, evolution of pollution	damage and policy cost	social planner, optimal timing RO	uncertain benefits increase the option to postpone a policy intervention, good news increases regrets of an early intervention
Baranzini et al. (2003)	ratio of climate change benefits and cost	cost	social planner, sequential RO	delay of policy intervention shortened if a catastrophe is more likely
Lin et al. (2007)	like in Pindyck (2002) but correlated	damage, policy cost	social planner, optimal timing RO	option to wait increases with correlation and deviation of social cost but decreasing with the deviation of pollution
Ohyama and Tsujimura (2008)	Pindyck (2002), technological progress	damage, policy cost	two competing agents, optimal timing RO	simultaneous implementation of policy but higher threshold, leadership incentives possible

Table III: Timing of environmental policy under uncertainty

Source	Type of uncertainty	Irreversibility feature	Decision-maker and model	Main finding
Larson and Frisvold (1996)	pollution tax	R&D expenditure	single firm, two-period sequential RO	increasing tax uncertainty encourages investment if this implies a lower responsiveness to future prices
Farzin and Kort (2000)	pollution tax	installation equipment	single firm, time-continuous stochastic control	expectation of increasing tax boosts investments, there is no certainty-equivalent discount rate for policy timing
Baker and Shittu (2006)	carbon tax	-	single firm, two-period stochastic control model	R&D does not increase monotonically with an expected carbon tax, investment in alternative R&D increases if inputs are good substitutes, investments into carbon-technologies generally decrease with risks of tax increases
Isik (2004)	cost-share subsidies, cost investment and its value	investments	single firm, optimal timing RO	adoption of site-specific technologies is accelerated (delayed) if the risk of stopping (starting) R&D support increases

Table IV: Impact of policy uncertainty

Source	Type of uncertainty	Irreversibility feature	Decision-maker and model	Main finding
Chao and Wilson (1993)	emission demand	investment in scrubbers	social planner, time-continuous RO	market uncertainty drives the permit price creating a large option value, flexible allowances are preferred
Baker and Adu-Bonnah (2008)	catastrophic events, technological progress	-	social planner, stochastic growth model	optimal R&D depends on the type of technology (fossil/non-fossil), risky R&D is high if a catastrophe is unlikely
Blanford (2009)	R&D paths	-	social planner, energy-economy model MERGE	social value of technological progress depends on the market share of technologies, policy diversification is optimal
Bosetti and Tavoni (2009)	carbon-free backstop	investments	social planner, two-period growth model combined with WITCH	uncertainty causes a higher optimal R&D level, risk hedging by technologies is possible

Table V: Optimal environmental policy under uncertain technological progress I

Source	Type of uncertainty	Irreversibility feature	Decision-maker and model	Main finding
Bosetti et al. (2009)	abatement cost	energy substitutionability	social planner, climate model WITCH	the optimal level of R&D is higher under uncertainty, price instruments induce more energy R&D
Goeschl and Perino (2009)	impact, technological advance	investments	social planner, growth model	a step-by-step policy is optimal, innovation is not only driven by environmental concerns, technological uncertainty lowers welfare
Ansar and Sparks (2009)	adoption benefits, catastrophes	investments	firm and aggregate level, optimal timing RO	experience curve can explain high implicit discount rates, high investment hurdle rates, option to wait
Fuss (2010)	fuel price, technological progress	investments	electricity sector, optimal timing RO	price volatility is less important, switching to wind farms not in the short-run

Table VI: Optimal environmental policy under uncertain technological progress II

A.3. Appendix to the basic model and its solution

A.3.1. Derivation of the variance of the expected cost to completion

The variance of a random variable X is defined as

$$\begin{aligned}\mathcal{V}ar(X) &= \int (x-\mu)^2 f(x)dx \\ &= \int x^2 f(x)dx - 2\mu \int x f(x)dx + \mu^2 \int f(x)dx \\ &= \mathcal{E}[X^2] - \mu^2 \ . \end{aligned} \tag{A.3}$$

$f(x)$ is the distribution function and $\mu = \mathcal{E}(X) = \int x f(x)dx$ is the expectation value of X (first moment functional). This transformation uses the normalisation property $\int f(x)dx = 1$.

For Eq. (3.1) with specification Eq. (3.2), the expected cost to completion is $K(t) = \mu$ (see the Appendix of Pindyck (1993)). $E[X^2]$ equals the second moment ($n = 2$) of the hierarchy of functionals U_n that describe the random variable K. See Karlin and Taylor (1981, p. 203) for the derivation of the general formula. The second moment is given by

$$E[X^2]_{X=K} = U_2(K) = E_K\left[\left(\int_0^{\tilde{T}} I d\tau | K\right)^2\right] \ . \tag{A.4}$$

Remember, $K(t)$ is $dK = \nu dt + \sigma dw = -I dt + \gamma\sqrt{IK}dw_t$. The second moment of K (short: $U_2(K) = U(K)$) has to solve the corresponding Kolmogorov-Equation

$$0 = \frac{1}{2}\sigma^2(K)U_{KK}(K) + \nu U_K(K) + 2\mu(K)I \tag{A.5}$$

$$= \frac{1}{2}\gamma^2 IKU_{KK}(K) - IU_K(K) + 2KI \ , \tag{A.6}$$

with boundary conditions

$$U_2(0) = 0 \ \text{ and } \ U_2(\infty) = \infty \ . \tag{A.7}$$

The Kolmogorov-Equation is satisfied by

$$U_2(K) = \frac{2}{2-\gamma^2}K^2 \ , \tag{A.8}$$

as long as $\gamma^2 < 2$ and $I \neq 0$. The condition on γ tests if K can be described by a controlled diffusion process, i.e. fluctuations are thereby limited. Otherwise, another process has to be used. Inserting the result for $U_2(K)$ in the definition of variance $\mathcal{V}ar(K)$ gives Eq. (3.3).

To proof that (A.8) satisfies the Kolmogorov-Equation (A.6), we use a power law Ansatz

$$U = a\,K^b \ ,$$

with $U_K = a\,b\,K^{b-1}$ and $U_{KK} = a\,b\,(b-1)\,K^{b-2}$. Inserting into (A.6) gives

$$K^{2-b} = \gamma^2/4\ a\,b\,(1-b) + a\,b/2 \ \text{ for } \ K > 0.$$

This has to be satisfied for all $K > 0$. Setting e.g. $K = 1$ and $K = 2$, it must hold that

$$1^{2-b} = 2^{2-b} \ ,$$

This is only true if $b = 2$. Inserting $b = 2$ back e.g. for $K = 1$ shows that $\alpha = 2/(2-\gamma^2)$. Boundary conditions are also satisfied.

Relationship between variance of random variable K and the Kolmogorov equation

The increments of random variable $K(t)$ are given by a controlled diffusion process with control I

$$dK = \nu(K, I)dt + \sigma(K, I)dw_t = -Idt + \gamma\sqrt{IK}dw_t \ .$$

The second moment of the probability distribution for K (=variance of K) is defined as Eq. (A.3)

$$\mathcal{V}ar(K) = \mathcal{E}[K^2] - E(K)^2 \ ,$$

with the first moment of the probability distribution (=expectation value of K)

$$E(K) = \int k\, f(k)dk \ ,$$

and the second moment of a functional $U(K)_{n=2}$, Eq. (A.4),

$$E[K^2] = U(K) = E_K\left[\left(\int_0^{\tilde{T}} Id\tau|K\right)^2\right] \ .$$

This equation describes the expectation value of hitting a border value at time T under control I conditional on K.

We want to sketch that $U(K)$ has to solve the Kolmogorov equation, Eq. (A.6), see Karlin and Taylor (1981), p. 191 ff. and p. 202 ff.

We start by considering a general functional $U(x)$ of random variable x with $x = X(0)$, as in Karlin and Taylor (1981), Eq. (3.31). $U(x)$ is the probability distribution for an integrated function $g(X(t))$ (=control) at which a border is reached by x. This defines hitting time T. In case the functional is specified with $f(x) = x^n$, random variable $Z = \int_0^T g(X(\tau))d\tau$ can be described by moments generated through n.

We look for the general solution of $U(x)$. Choosing a sufficiently short time duration h, $U(x)$ is developed by a Taylor expansion (Karlin and Taylor (1981), Eq. (3.33)). Using the Markov property, the law of total probabilities, and retaining all contributions up to order $o(h)$, one arrives at a general Kolmogorov equation for $U(x)$ (Karlin and Taylor (1981), Eq. (3.37)).

The nth moment of Z using $U(x)$ is considered after Karlin and Taylor (1981), Eq. (3.37). In case $f(x) = x^n$, the now specified functionals $U_n(x)$ fulfill a simplified Kolmogorov equation, see Karlin and Taylor (1981) Eq. (3.38=3.37'). With $x = K$, $g = I$, and $n = 2$, we arrive at Eqs. (A.5) and (A.6).

To summarize, the Kolmogorov equation can be associated with a functional that describes a hitting time random variable. The differential equation is obtained when approximating the functional (integral equation) with a Taylor distribution and using properties of diffusion processes.

A.3.2. Elimination of the singularity in Eq. (3.12)

The elimination of singularity in Eq. (3.12) is done by substituting $x = \ln K$ or $K = \exp(x)$. We obtain

$$\begin{aligned} f(x) &\equiv (F \circ \exp)(x) = F(K) \ , \\ F'(K) &= \frac{\partial f(x)}{\partial x}\frac{\partial x}{\partial K} = f'(x)\frac{1}{K} = f'(x)\exp(-x) \ , \\ F''(K) &= \frac{\partial F'(K)}{\partial K} = \left[f''(x)\exp(-x) - f'(x)\exp(-x)\right]\exp(-x) \ . \end{aligned} \tag{A.9}$$

With the help of these expressions, we transform the boundary conditions Eqs. (3.14, 3.15) and Eq. (3.12). For the former, we use for $K \to 0$ and $K \to \infty$, $x \to -\infty$ and $x \to \infty$, respectively. The latter transforms the second-order differential equation for $I \neq 0$ into a system of coupled first order differential equations. For $K < K^*$ and using $g(x) = f'(x)$ and $g'(x) = f''(x)$, we obtain

$$\begin{aligned} g'(x) &= \frac{2}{\gamma^2}\left[1 + g(x)\exp(-x) + \frac{r}{I_{\max}} f(x)\right]\exp(x) + g(x) \ , \\ f'(x) &= g(x) \ , \end{aligned} \tag{A.10}$$

where $f(-\infty) = V$, $f(x^*) = 0$, and $g(x^*) = 0$. The singularity at $K = 0$ has now been shifted to $\delta = 0.5$.

A.3.3. Fortran code for the numerical solution of the basic model

This is a simple code to show the principles of the numerical solution, it has not been optimised to minimise the numerical expense. The programme output reproduces comparative statistics for the basic model illustrated in Fig. 3.5. Results are accurate at least up to the second digit after the decimal place. The programme uses the root finding routine dzerox and the Runge-Kutta-Merson routing dqmr from the CERN library programme repository (CERN).

```
!===========================================================================
!  Programme code for the basic sequential investment model in Sec. 3.3  *
!  to solve the set of linear differential equations Eqs. (3.16 )        *
!  for  f(x) within -infty <= x <= x*                                    *
!       g'(x) = 2/gamma/gamma( 1+g(x)exp(-x)+r/Imax f(x) )exp(x)+g(x)    *
!       f'(x) = g(x)                                                     *
!  with boundary conditions (free boundary x=x*):                        *
!       f(-infty)=V     f(x*)=0      g(x*)=0                             *
!  Method: Runge-Kutta-Merson, Output: exp(x*) as f(parameters)          *
!===========================================================================
module params
  implicit none
  real*8 :: gamma,r,V,RR
end module params
!===========================================================================
! MASTER: 1) Definition of Parameters, 2) Runge-Kutta-Merson to find     *
!         root and 3) plot output                                        *
!===========================================================================
program gbsopt
  use params
  implicit none
  integer :: i,j,mm,maxf,mode
  real*8 :: aa,bb,eps,dzerox,finit,res
  external finit
!---------------------------------------------------------------------------
! 1) PARAMETERS                                                          *
! gamma .. overall technical uncertainty                                 *
! r     .. discount rate                                                 *
! RR    .. upper boundary of investment constraint (Imax in Chapter 3)   *
! V     .. payoff after completion                                       *
!---------------------------------------------------------------------------
  !gamma=1.0d0
  r=0.05d0
  RR=2.0d0
  V=10.0d0
! loop from j to mmm over parameter of choice
  mm=1000
 do j=1,mm
  gamma=1.4d0*dble(j)/dble(mm)
  !r=0.1d0*dble(j)/dble(mm)
  !RR=20.0d0*dble(j)/dble(mm)
  !V=20.0d0*dble(j)/dble(mm)
```

```
!-----------------------------------------------------------------------------
! 2) Starts shooting by calling dzerox() from CERNLIB: returns zero of   *
! function finit in intervall (aa,bb) with accuracy eps, MAXF - max      *
! references in loop to finit, mode - two choices for finding algorithm  *
!-----------------------------------------------------------------------------
  aa=-10.0d0
  bb=10.0d0
  eps=1.0d-6
  maxf=50
  mode=1
  res=dzerox(aa,bb,eps,maxf,finit,mode)
!-----------------------------------------------------------------------------
! 3) Output                                                               *
!-----------------------------------------------------------------------------
  print '(3e12.4)',gamma,dexp(res)
 end do
end program gbsopt
! ===========================================================================
! Zero of this function establishes correct boundary in -infinity (x2)   *
! using dqmr() from CERNLIB: solves simult. first-order differential     *
! eqations with Runge-Kutta-Merson, n - number of eq., h0 - step length, *
! eps - accuracy, sub - set of eqs. defined externally, w - workspace    *
!============================================================================
real*8 function finit(x)
  use params
  implicit none
  integer :: n
  parameter (n=2)
  real*8 :: x,x1,x2,h0,eps
  real*8, dimension(n) :: y
  real*8, dimension(6*n) :: w
  external sub
!
  x1=x
  x2=-10.0d0
  y(1)=0.0d0
  y(2)=0.0d0
  h0=1.0d-2
  eps=1.0d-3
  call ddeqmr(n,x1,x2,y,h0,eps,sub,w)
  write(11,*) x,y(2)-V
  finit=y(2)-V
end function finit
```

```
!=========================================================================
! Set of linear differential equations                                   *
!=========================================================================
subroutine sub(x,y,f)
  use params
  implicit none
  real*8 :: x
  real*8, dimension(2) :: y,f
!
  f(1)=2.0d0/gamma**2*(1.0d0+y(1)*dexp(-x)+r/RR*y(2))*dexp(x)+y(1)
  f(2)=y(1)
end subroutine sub
```

A.3.4. Results

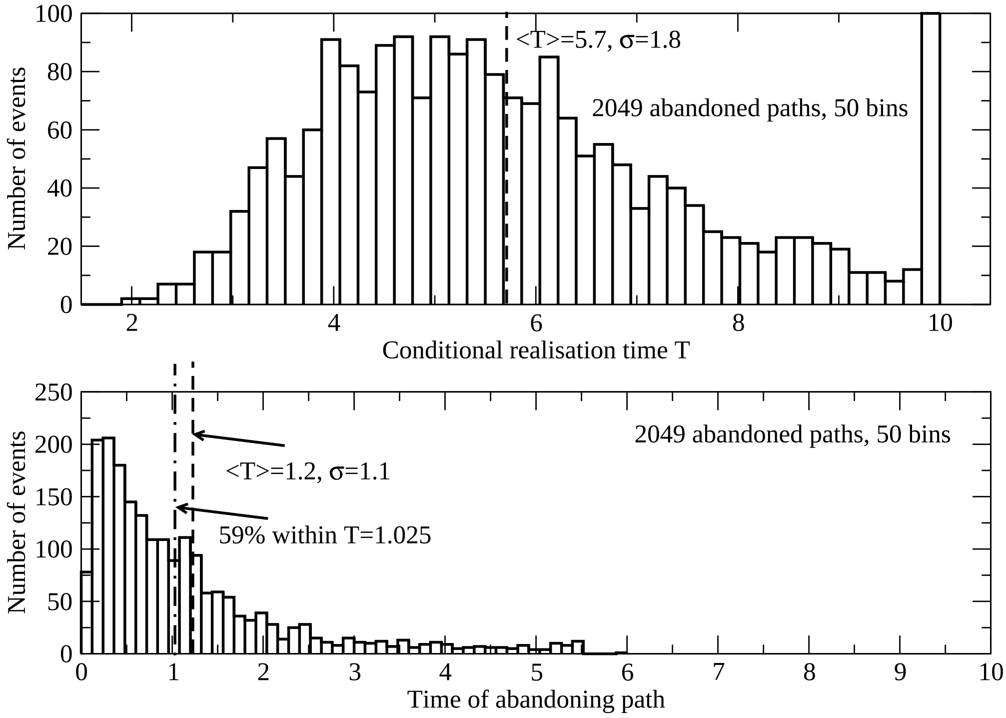


Figure A.1.: Histograms of abandoned paths (n=2049) for $\gamma = 0.5$, $I = 2$, $V = 10$, $r = 0.05$, total simulation time $t = 10$, number of time steps $m = 30000$, number of paths 10000. Means are given in <>, and σ is the standard deviation.

A.4. An application to offshore windfarm investment

A.4.1. Offshore windfarm data

Name	Country	Year	I [MEUR]	C [MW]	TS [m]	#	D [m]	Dt [m]
Vindeby	DK	1991	7.615	5	0.45	11	3.5	1500
Lely	NL	1994	3.264	2	0.50	4	7.5	800
Tuno Knob	DK	1995	7.615	5	0.50	10	4	3000
Dronten	NL	1996	19.445	11	0.60	19	1.5	30
Bockstigen	SE	1997	3.264	3	0.55	5	6	3000
Blyth	UK	2000	4.759	4	2.00	2	8.5	1000
Middlegrunden	DK	2001	36.035	40	2.00	20	6	2000
Utgrunden	SE	2001	9.519	10	1.43	7	8.6	7000
Yttre Stengrund	SE	2001	12.238	10	2.00	5	8	4000
Horns Rev	DK	2002	339.951	160	2.00	80	10	14000
Nysted	DK	2003	253.603	158	2.30	72	7.75	10000
Samso	DK	2003	35.355	23	2.30	10	20	3500
North Hoyle	UK	2003	100.626	60	2.00	30	12	7000
Ronland	DK	2003	17.677	17.2	2.30	8	1	100
Scroby Sands	UK	2004	105.385	60	2.00	30	16.5	2500
Arklow	IE	2004	47.593	25	3.60	7	3.5	10000
Kentish Flats	UK	2005	147.539	90	3.00	30	5	10000
Barrow	UK	2006	129.181	90	3.00	30	17.5	7500
Egmond aan Zee	NL	2006	227.087	108	3.00	36	18	10000
Burbo Bank	UK	2007	125.782	90	3.60	25	5	6500
Lillgrund	SE	2007	203.971	110	2.30	48	7	10000
Q7	NL	2007	401.142	120	2.00	60	21.5	23000
Beatrice	UK	2007	47.593	10	5.00	2	45	22000
Robin Rigg	UK	2008	520.125	2890	3.00	60	5	9000
Thornton bank	BE	2008	849.878	2833	5.00	60	14	27000
Inner Dowsing	UK	2008	203.971	2103	3.60	25	10	5200
Lynn	UK	2008	203.971	2103	3.60	27	10	5200

Table A.2.: European offshore wind parks. Data given in the columns are the name and country of the wind park, the year of its operation start, investment cost (I) in Million Euro, capacity (C) in Mega Watt, turbine size (TS) in meter, number of turbines per park (#), water depth of the foundation (D) in meter, distance from shore (Dt) in meter. Sources: Snyder and Kaiser (2009b); DENA (2010); KPMG (2007); EWEA (2009).

A.4.2. Results

		$F(K)$				K^*			
Distance:		15 km		16 km		15 km		16 km	
T	$\mathcal{P}$	O&M high	O&M low	O&M high	O&M low	O&M high	O&M low	O&M high	O&M low
1.5	(1)	22.580	81.694	18.205	77.318	156.963	214.412	157.181	214.815
	(2)	10.293	103.810	5.918	99.434	144.788	235.441	144.974	235.925
	(3)	0	0	0	0	-	40.501	-	40.516
	(4)	0	0	0	0	-	63.657	-	63.693
2 y.	(1)	20.409	78.064	16.087	73.742	154.780	210.406	155.060	210.918
	(2)	8.426	99.634	4.104	95.312	142.923	230.640	143.163	231.253
	(3)	0	0	0	0	-	40.350	-	40.370
	(4)	0	0	0	0	-	63.288	-	63.336
3 y.	(1)	16.266	71.109	12.049	66.891	150.644	202.954	151.037	203.654
	(2)	4.867	91.627	0.650	87.409	139.378	221.766	139.715	222.596
	(3)	0	0	0	0	-	40.054	-	40.082
	(4)	0	0	0	0	-	62.566	-	62.636
4 y.	(1)	12.376	64.544	8.260	60.427	146.787	196.155	147.276	197.010
	(2)	1.533	84.061	0	79.945	136.055	213.732	136.477	214.739
	(3)	0	0	0	0	-	39.763	-	39.800
	(4)	0	0	0	0	-	61.866	-	61.956
5 y.	(1)	8.725	58.348	4.706	54.330	143.179	189.920	143.752	190.903
	(2)	0	76.914	0	72.895	132.932	206.414	133.429	207.565
	(3)	0	0	0	0	-	39.477	-	39.523
	(4)	0	0	0	0	-	61.186	-	61.295
6 y.	(1)	5.300	52.504	1.377	48.580	139.793	184.17	140.44	185.265
	(2)	0	70.164	0	66.240	129.990	199.711	130.553	200.980
	(3)	0	0	0	0	-	39.197	-	39.252
	(4)	0	0	0	0	-	60.525	-	60.653

Table A.3.: Value of investment $F(K)$ and critical investment cost K^* for $\gamma = 0$. Four policy regimes $\mathcal{P}$ are considered. (1) sprinter bonus, running time: 20 years; (2) sprinter bonus, running time: ∞; (3) basis tariff, running time: 20 years; (4) basis tariff, running time: ∞.

		K^* ($\gamma = 0.503$)		K^* ($\gamma = 0.489$)		K^* ($\gamma = 0.8$)		K^* ($\gamma = 0.8$)	
Distance:		15 km		16 km		15 km		16 km	
T	$\mathcal{P}$	O&M high	O&M low	O&M high	O&M low	O&M high	O&M low	O&M high	O&M low
1.5 y.	(1)	177.6	243.0	176.7	241.8	209.0	286.3	209.2	286.8
	(2)	163.8	267.0	162.9	265.7	192.6	314.7	192.8	315.3
	(3)	-	45.7	-	45.4	-	53.58	-	53.59
	(4)	-	71.8	-	71.4	-	84.32	-	84.36
2 y.	(1)	175.4	238.9	174.5	237.9	206.6	282.2	206.9	282.5
	(2)	161.9	262.0	161.1	261.0	190.6	309.5	190.9	310.2
	(3)	-	45.5	-	45.3	-	53.4	-	53.4
	(4)	-	71.5	-	71.1	-	83.9	-	84.0
3 y.	(1)	171.1	231.2	170.4	230.4	202.1	273.8	202.5	274.6
	(2)	158.2	252.9	157.6	252.1	186.8	299.8	187.1	300.7
	(3)	-	45.22	-	45.0	-	53.1	-	53.1
	(4)	-	70.7	-	70.4	-	83.2	-	83.2
4 y.	(1)	167.2	224.2	166.6	223.6	197.9	266.2	198.4	267.2
	(2)	154.8	244.6	154.2	244	183.1	290.8	183.6	291.9
	(3)	-	44.93	-	44.7	-	52.8	-	52.8
	(4)	-	70.1	-	69.7	-	82.4	-	82.5
5 y.	(1)	163.4	217.7	162.9	217.2	193.9	259.3	194.5	260.4
	(2)	151.6	237.0	151.1	236.5	179.7	282.6	180.2	283.9
	(3)	-	44.6	-	44.4	-	52.5	-	52.5
	(4)	-	69.3	-	69.0	-	81.7	-	81.8
6 y.	(1)	159.9	211.7	159.5	211.4	190.1	252.8	190.8	254.0
	(2)	148.6	230.0	148.1	229.7	176.4	275.0	177.0	276.4
	(3)	-	44.4	-	44.1	-	52.2	-	52.2
	(4)	-	68.6	-	68.3	-	81.0	-	81.1

Table A.4.: Critical investment cost K^* for different values of technical uncertainty γ. Four policy regimes $\mathcal{P}$ are considered. (1) sprinter bonus, running time: 20 years; (2) sprinter bonus, running time: ∞; (3) basis tariff, running time: 20 years; (4) basis tariff, running time: ∞.

		$F(K)$ ($\gamma = 0.503$)		$F(K)$ ($\gamma = 0.489$)		$F(K)$ ($\gamma = 0.8$)		$F(K)$ ($\gamma = 0.8$)	
Distance:		15 km		16 km		15 km		16 km	
T	$\mathcal{P}$	O&M high	O&M low	O&M high	O&M low	O&M high	O&M low	O&M high	O&M low
1.5	(1)	24.9	82.6	20.8	78.2	32.2	86.6	28.9	82.7
	(2)	14.1	104.6	10.4	100.2	22.1	108.0	19.2	104.0
	(3)	0	0	0	0	0	0	0	0
	(4)	0	0	0	0	0	0	0	0
2 y.	(1)	23.1	79.2	19.9	74.8	30.7	83.7	27.6	78.8
	(2)	12.7	100.72	9.2	96.4	20.9	104.6	18.1	100.7
	(3)	0	0	0	0	0	0	0	0
	(4)	0	0	0	0	0	0	0	0
3 y.	(1)	19.8	72.7	16.0	68.6	27.9	78.2	24.9	74.5
	(2)	10.2	93.3	6.9	89.1	18.8	98.1	16.1	94.3
	(3)	0	0	0	0	0	0	0	0
	(4)	0	0	0	0	0	0	0	0
4 y.	(1)	16.7	66.8	13.1	62.7	25.4	73.1	22.5	69.5
	(2)	7.9	86.2	5.0	82.1	16.7	92.1	14.2	88.3
	(3)	0	0	0	0	0	0	0	0
	(4)	0	0	0	0	0	0	0	0
5 y.	(1)	13.9	61.2	10.4	57.1	23.0	68.3	20.3	64.8
	(2)	5.9	79.6	3.3	75.6	14.9	86.2	12.6	82.8
	(3)	0	0	0	0	0	0	0	0
	(4)	0	0	0	0	0	0	0	0
6 y.	(1)	11.3	55.8	8.2	51.9	20.8	63.8	18.2	60.4
	(2)	4.2	73.5	2	69.5	13.2	81	11.0	77.5
	(3)	0	0	0	0	0	0	0	0
	(4)	0	0	0	0	0	0	0	0

Table A.5.: Value of investment $F(K)$ for different values of technical uncertainty γ. Four policy regimes $\mathcal{P}$ are considered. (1) sprinter bonus, running time: 20 years; (2) sprinter bonus, running time: ∞; (3) basis tariff, running time: 20 years; (4) basis tariff, running time: ∞.

T [a]		$\gamma = 0$ O&M high	$\gamma = 0$ O&M low	$\gamma = 0.493$ O&M high	$\gamma = 0.493$ O&M low
1.5	K^*	157.2	214.8	176.7	241.8
	F(K)	18.2	77.3	20.8	78.2
2	K^*	155.1	210.9	174.5	237.9
	F(K)	16.1	73.7	19.9	74.8
6	K^*	140.4	185.3	159.5	211.4
	F(K)	1.4	48.6	8.2	51.9

T [a]	$\gamma = 0$ O&M high	$\gamma = 0$ O&M low	$\gamma = 0.493$ O&M high	$\gamma = 0.493$ O&M low
1.5	157.2	214.8	176.7	241.8
2	155.1	210.9	174.5	237.9
3	151.0	203.7	170.4	230.4
4	147.3	197.0	166.6	223.6
5	143.8	190.9	162.9	217.2
6	140.4	185.3	159.5	211.4
$\langle K^* \rangle$	149.1	200.4	168.4	227.0
σ [%]	4	6	4	5

Table A.6.: Value of investment $F(K)$ and critical investment cost K^* in MEUR for Baltic 1. 16 km distance from offshore and total investment $I = 139.1$ MEUR. Dependence of K^* on the construction time T in years [a] and technical uncertainty parameter γ. Policy scheme: sprinter bonus for the first 12 years, afterwards basis feed-in tariff, running time of the wind park: 20 years.

T [a]		$\gamma = 0$ O&M high	$\gamma = 0$ O&M low	$\gamma = 0.503$ O&M high	$\gamma = 0.503$ O&M low
1.5	K^*	157.0	214.4	177.6	243.0
	F	22.6	81.7	24.9	82.6
2	K^*	154.8	210.4	175.4	238.9
	F	20.4	78.1	23.1	79.2
6	K^*	139.8	184.2	159.9	211.7
	F	5.3	52.5	11.3	55.8

T [a]	$\gamma = 0$ O&M high	$\gamma = 0$ O&M low	$\gamma = 0.503$ O&M high	$\gamma = 0.503$ O&M low
1.5	157.0	214.4	177.6	243.0
2	154.8	210.4	175.4	238.9
3	150.6	203.0	171.1	231.2
4	146.8	196.2	167.2	224.2
5	143.2	189.9	163.4	217.7
6	139.8	184.2	159.9	211.7
$\langle K^* \rangle$	148.7	199.7	169.1	227.8
σ [%]	4	6	4	5

Table A.7.: Value of investment $F(K)$ and critical investment cost K^* in MEUR for Baltic 1. 15 km distance from offshore and total investment $I = 134.5$ MEUR. Dependence of K^* on the construction time T in years [a] and technical uncertainty parameter γ. Policy scheme: sprinter bonus for the first 12 years, afterwards basis feed-in tariff, running time of the wind park: 20 years.

A.5. An application to environmental R&D decisions

A.5.1. Derivation of Eqs. (3.30, 3.31-3.32)

We are using a Cobb-Douglas production function of the form

$$q(E,L) = \theta(\phi_0 E)^{\alpha} L^{\beta}, \;\; \alpha,\beta \leq 0, \;\; \alpha+\beta < 1 \;\;, \tag{A.11}$$

with output q, inputs E (energy) and L (labour). Parameter ϕ_0 describes the efficiency of the use of energy in the initial stage, θ is a general productivity parameter, and α and β are the production elasticities of inputs.

To set both policy regimes $k = \{\mathcal{T}, \mathcal{Q}\}$ to the same level of energy use we first determine the profit maximising tax rate τ. Profits using the current technology are given by

$$\pi_0^k(E,L) = \underbrace{Pq(\phi_0,E,L)}_{benefits} - \underbrace{(z+\tau)E}_{energy\,costs} - \underbrace{wL}_{labour\,costs} \;\;, \tag{A.12}$$

where P is the constant output price, z is the constant energy price, and w is the constant wage rate.

To solve the maximisation problem for the tax regime, we determine the partial derivatives and set them equal to zero. We obtain

$$\begin{array}{lll} \frac{\partial}{\partial L}\pi_0^{\mathcal{T}}(E,L) = P\theta\phi_0^{\alpha}E^{\alpha}\beta L^{\beta-1} - w = 0 & \Rightarrow & E^{\alpha} = \frac{1}{P\theta}\frac{w}{\beta}\frac{1}{\phi_0^{\alpha}}\frac{1}{L^{\beta-1}} \\ \frac{\partial}{\partial E}\pi_0^{\mathcal{T}}(E,L) = P\theta\phi_0^{\alpha}\alpha E^{\alpha-1}L^{\beta} - (z+\tau) = 0 & \Rightarrow & E^{\alpha-1} = \frac{z+\tau}{P\theta}\frac{1}{\alpha}\frac{1}{\phi_0^{\alpha}}\frac{1}{L^{\beta}} \end{array} \;. \tag{A.13}$$

Next, we use one equation to substitute E in the other. This gives L as a function of only parameters

$$L = \left[P\theta\left(\frac{\beta}{w}\right)^{1-\alpha}\left(\frac{\alpha}{z+\tau}\right)^{\alpha}\right]^{\frac{1}{1-\alpha-\beta}} \phi_0^{\frac{\alpha}{1-\alpha-\beta}} \;. \tag{A.14}$$

Using the same procedure and substituting L in $E^{\alpha-1}$ derives E as a function of only parameters

$$E = \left[P\theta\left(\frac{\beta}{w}\right)^{\beta}\left(\frac{\alpha}{z+\tau}\right)^{1-\beta}\right]^{\frac{1}{1-\alpha-\beta}} \phi_0^{\frac{\alpha}{1-\alpha-\beta}} \;. \tag{A.15}$$

These are the optimal inputs of energy and labour for a given tax rate τ. The optimal energy input under the tax regime also defines the energy quota for the quota regime, Eq. (3.30).

Profit flows for the tax regime can now be calculated by inserting E and L, Eqs. (A.14, A.15), into $\pi_i^{\mathcal{T}}$ (replacing ϕ_0 with ϕ_i). We get

$$\pi_i^{\mathcal{T}} \;\; = \;\; P\theta\phi_i^{\alpha}\left[P\theta\left(\frac{\beta}{w}\right)^{\beta}\left(\frac{\alpha}{z+\tau}\right)^{1-\beta}\right]^{\frac{\alpha}{1-\alpha-\beta}} \phi_i^{\frac{\alpha\alpha}{1-\alpha-\beta}}$$

$$
\begin{aligned}
&\times \quad \left[P\theta\left(\frac{\beta}{w}\right)^{1-\alpha}\left(\frac{\alpha}{z+\tau}\right)^{\alpha}\right]^{\frac{\beta}{1-\alpha-\beta}} \phi_i^{\frac{\alpha\beta}{1-\alpha-\beta}} \\
&- \quad (z+\tau)\left[P\theta\left(\frac{\beta}{w}\right)^{\beta}\left(\frac{\alpha}{z+\tau}\right)^{1-\beta}\right]^{\frac{1}{1-\alpha-\beta}} \phi_i^{\frac{\alpha}{1-\alpha-\beta}} \\
&- \quad w\left[P\theta\left(\frac{\beta}{w}\right)^{1-\alpha}\left(\frac{\alpha}{z+\tau}\right)^{\alpha}\right]^{\frac{\alpha}{1-\alpha-\beta}} . \qquad \text{(A.16)}
\end{aligned}
$$

It is possible to factor out $\phi_i^{\frac{\alpha}{1-\alpha-\beta}} := \phi_i^{\gamma^{\mathcal{T}}}$ and $(P\theta)^{\frac{1}{1-\alpha-\beta}} := (P\theta)^{\gamma^{\mathcal{T}}/\alpha}$. Other terms can be merged. After some calculation, we optain Eq. (3.31, $k = \mathcal{T}$)

$$
\begin{aligned}
&\pi_i^{\mathcal{T}} = \\
&= \quad \phi_i^{\gamma^{\mathcal{T}}}(P\theta)^{\gamma^{\mathcal{T}}/\alpha}\left\{\left[\left(\frac{\alpha}{z+\tau}\right)^{\alpha}\left(\frac{\beta}{w}\right)^{\beta}\right]^{\gamma^{\mathcal{T}}/\alpha}\right. \\
&- \quad \left.\left[(z+\tau)^{1-\alpha-\beta}\left(\frac{\alpha}{z+\tau}\right)^{1-\beta}\left(\frac{\beta}{w}\right)^{\beta}\right]^{\gamma^{\mathcal{T}}/\alpha} - \left[w^{1-\alpha-\beta}\left(\frac{\alpha}{z+\tau}\right)^{\alpha}\left(\frac{\beta}{w}\right)^{1-\alpha}\right]^{\gamma^{\mathcal{T}}/\alpha}\right\} \\
&= \quad \phi_i^{\gamma^{\mathcal{T}}}(P\theta)^{\gamma^{\mathcal{T}}/\alpha}\left[\frac{1}{(z+\tau)^{\alpha}}\frac{1}{w^{\beta}}\right]^{\gamma^{\mathcal{T}}/\alpha} \\
&\times \quad \left\{\left[\alpha^{\alpha}\beta^{\beta}\right]^{\gamma^{\mathcal{T}}/\alpha} - \left[\alpha^{1-\beta}\beta^{\beta}\right]^{\gamma^{\mathcal{T}}/\alpha} - \left[\alpha^{\alpha}\beta^{1-\alpha}\right]^{\gamma^{\mathcal{T}}/\alpha}\right\} \\
&= \quad \underbrace{[1-\alpha-\beta]\left[P\theta\left(\frac{\alpha}{z+\tau}\right)^{\alpha}\left(\frac{\beta}{w}\right)^{\beta}\right]^{\gamma^{\mathcal{T}}/\alpha}}_{\xi^{\mathcal{T}}} \phi_i^{\gamma^{\mathcal{T}}/\alpha} = \xi^{\mathcal{T}}\phi_i^{\gamma^{\mathcal{T}}} \quad .
\end{aligned}
$$

For the quota regime, we need to maximise Eq. (3.29) for L only as $E = \bar{E}$. Be reminded that $\bar{E}$ does not change and depends on ϕ_0. We get

$$
\begin{aligned}
\frac{\partial}{\partial L}\pi_i^{Q}(\phi_i) \quad &= \quad P\theta\phi_i^{\alpha}\bar{E}^{\alpha}\beta L^{\beta-1} - w = 0 \ , \\
\Rightarrow \quad L &= \left[\frac{w}{\beta}\frac{1}{P\theta}\frac{1}{\phi_i^{\alpha}}\frac{1}{\bar{E}^{\alpha}}\right]^{\frac{1}{\beta-1}} \quad . \qquad \text{(A.17)}
\end{aligned}
$$

Next, we insert L back into Eq. (3.29) merging terms. We can separate the factors $\phi_i^{-\frac{\alpha}{\beta-1}}$, $(P\theta)^{-\frac{1}{\beta-1}}$ and $\bar{E}^{-\frac{\alpha}{\beta-1}}$. Introducing the definition $\gamma^{\mathcal{Q}} := \alpha/(1-\beta)$ derives Eq. (3.31, $k = \mathcal{Q}$)

$$
\pi_i^{\mathcal{Q}} \quad = \quad \phi_i^{-\frac{\alpha}{\beta-1}}(P\theta)^{-\frac{1}{\beta-1}}\bar{E}^{-\frac{\alpha}{\beta-1}}\left\{\left(\frac{\beta}{w}\right)^{-\frac{\beta}{\beta-1}} - w^{\frac{\beta-1}{\beta-1}}\left(\frac{\beta}{w}\right)^{-\frac{1}{\beta-1}}\right\} - z\bar{E}
$$

$$= \underbrace{(1-\beta)\left[P\theta\bar{E}^{\alpha}\left(\frac{\beta}{w}\right)^{\beta}\right]^{\frac{1}{1-\beta}}}_{\xi^{\mathcal{Q}}} \phi_i^{\gamma^{\mathcal{Q}}} - z\bar{E} \ .$$

A.5.2. Deterministic case

Let $\gamma \to 0$ in Eq. (3.12)

$$rF(K) = -I\left(1 + \frac{\partial F(K)}{\partial K}\right) \ , \tag{A.18}$$

under investment constraint

$$I \ = \ \begin{cases} \pi_0^k & \text{if} \quad K < K^* \\ 0 & \text{if} \quad K > K^* \end{cases} \ , \tag{A.19}$$

and boundary conditions

$$F(0) = \pi_i^k/r \ , \quad \lim_{K\to\infty} F(K) = 0 \ , \quad F(K^*) = 0 \ , \quad F'(K^*) = 0 \ . \tag{A.20}$$

The ansatz for the solution is

$$F(K) = \frac{-I}{r} + C\exp\left(-\frac{K}{I}r\right) \ . \tag{A.21}$$

The first boundary condition determines constant C

$$C = \frac{\pi_i^k + I}{r} \ . \tag{A.22}$$

Derive K^* from $F(K^*) = 0$

$$K^* = \frac{I}{r}\ln\left[\frac{\pi_i^k + I}{I}\right] \ . \tag{A.23}$$

The second boundary condition is fulfilled if I is chosen to be 0 in the region of non-investment, otherwise $I = I_{\max} = \pi_0^k$.

A.5.3. Results

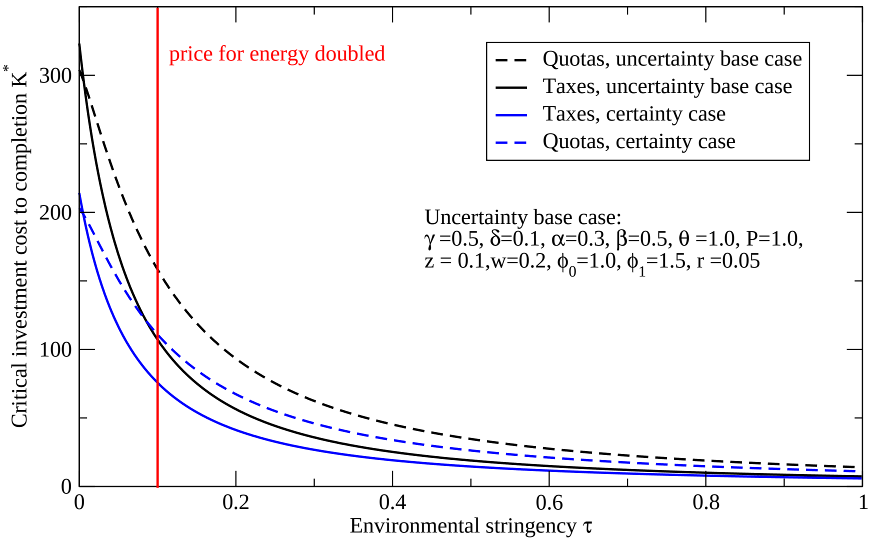


Figure A.2.: Critical investment cost K^* as a function of environmental stringency τ. Parameter values describe the base case.

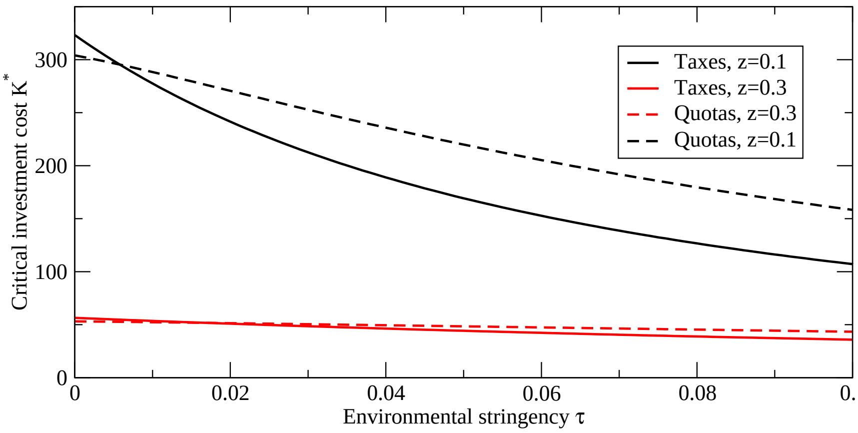


Figure A.3.: Critical investment cost K^* as a function of environmental stringency τ in dependence of the energy price z. Parameters are $\gamma = 0.5$, $\delta = 0.1$, $\alpha = 0.3$, $\beta = 0.5$, $w = 0.2$ and otherwise as given in Tab. 3.6.

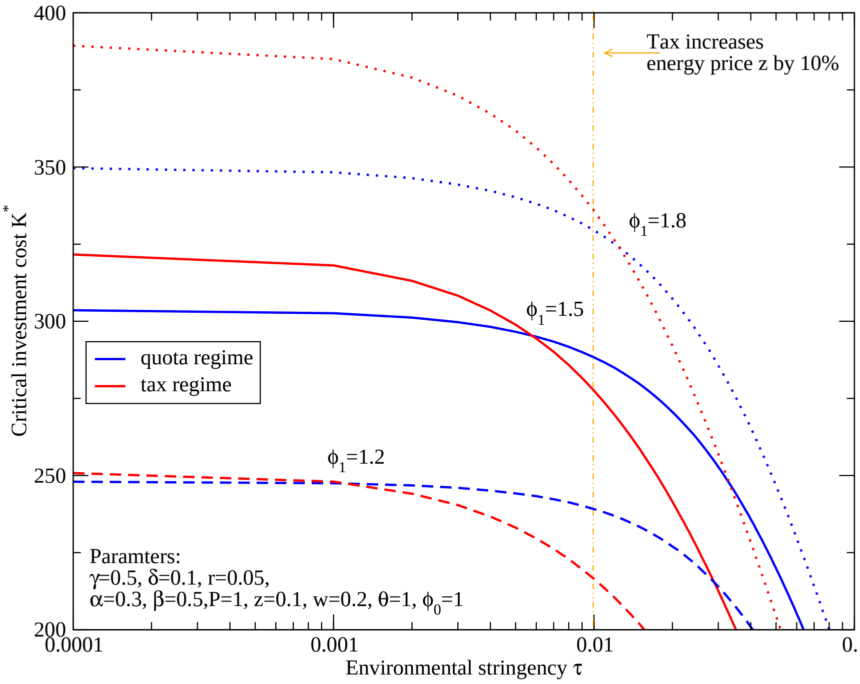


Figure A.4.: Critical investment cost K^* as a function of environmental stringency τ in dependence of future energy technology ϕ_1.

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Eidesstattliche Versicherung

Ich erkläre hiermit, dass ich die vorliegende Arbeit ohne unzulässige Hilfe Dritter und ohne Benutzung anderer als der angegebenen Hilfsmittel angefertigt habe; die aus fremden Quellen direkt oder indirekt übernommenen Gedanken sind als solche kenntlich gemacht.

Die Arbeit wurde bisher weder im Inland noch im Ausland in gleicher oder ähnlicher Form einer Prüfungsbehörde zur Erlangung eines akademischen Grades vorgelegt.

Valeria Jana Schwanitz
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