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Janne Kettunen

TEKNILLINEN KORKEAKOULU
TEKNISKA HÖGSKOLAN
HELSINKI UNIVERSITY OF TECHNOLOGY
TECHNISCHE UNIVERSITÄT HELSINKI
UNIVERSITE DE TECHNOLOGIE D'HELSINKI

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Helsinki University of Technology
Department of Engineering Physics and Mathematics
Systems Analysis Laboratory

Distribution:
Systems Analysis Laboratory
Helsinki University of Technology
P.O. Box 1100
FIN-02015 HUT, FINLAND
Tel. +358-9-451 3056
Fax +358-9-451 3096
systems.analysis@hut.fi

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Title: Applications of Stochastic Modeling for Investment Decision-Making under Market Uncertainties

Author: Janne Kettunen
University of Calgary
2500 University Drive NW
Calgary, Alberta T2N 1N4, Canada
jskettun@ucalgary.ca

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Abstract: Profit-seeking organizations make investment decisions with financial implications. These decisions are often complicated by (i) market uncertainties about investment payoffs, (ii) the possibility to select a portfolio of investments, and (iii) the presence of real options, which make it possible to postpone investments until some uncertainties are resolved. Quantitative support for these decisions builds on methodological contributions in stochastic modeling, financial modeling, and decision analysis, among others.

This dissertation develops scenario-based approaches and decision models for several problem contexts, most notably for (i) the optimal harvesting of forest stands, (ii) the management of electricity contract portfolios, (iii) the investments in power plants, and (iv) the valuation of real options in new product development. These models support investment decision-making and, in some cases, they also help analyze policy impacts at the industry level. Each model is presented in view of later publication in a refereed journal.

The methodological advances of the dissertation offer several novel insights into the above decision problems. In the context of the optimal harvesting of forest stands, this dissertation demonstrates that multi-level risk management over several time periods and at multiple confidence levels can reduce risks significantly without a major reduction in the expected return. In the management of electricity contract portfolios, the dissertation shows that correlation between price and load is important to model, or else risks may be underestimated, resulting in suboptimal decisions. In the analysis of the investments in power plants, it is concluded that uncertainties in the carbon dioxide emission policies may foster the development of more concentrated and less competitive electricity markets, because the new investments are more likely to be made by larger financially stronger incumbent firms than small, project-financed independent power producers. Finally, in the valuation of real options in new product development, the value of real options is shown to be non-monotonic with respect to increased competition, whereas the options for enhancing product development and delaying product launch are found to be typically most useful when the level of competition is weak.

Keywords: Decision analysis, investment appraisal, stochastic optimization, portfolio optimization, real options, risk management, scenario generation

Otsikko: Stokastisen mallintamisen sovelluksia investointipäätöksenteossa markkinaepävarmuuksien vallitessa

Tekijä: Janne Kettunen
University of Calgary
2500 University Drive NW
Calgary, Alberta T2N 1N4, Canada
jskettun@ucalgary.ca

Päiväys: Lokakuu 2009

Tiivistelmä: Voittoa tavoittelevat organisaatiot tekevät investointipäätöksiä, jotka vaikuttavat niiden taloudelliseen menestykseen. Tällaiset päätökset ovat usein haastavia, koska (i) markkinaepävarmuudet vaikuttavat tuottoon, (ii) sijoituksista on mahdollista muodostaa portfoliota ja (iii) reaalioptiot voivat sallia päätöksen lykkäämisen, kunnes osa epävarmuudesta on hälvennyt. Näiden päätösten kvantitatiivisessa tukemisessa tarvitaan muun muassa stokastista mallintamista, investointiteoriaa ja päätösanalyysiä.

Väitöskirjassa kehitetään skenaariopohjaisia menetelmiä sekä päätösmalleja useaan päätösongelmaan, erityisesti (i) metsien optimaaliseen hakkuuseen, (ii) sähkösopimusportfolion hallintaan, (iii) voimalaitoksien investointipäätöksiin ja (iv) reaalioptioiden arvottamiseen tuotekehitysprojektissa. Nämä mallit tukevat investointipäätöksentekoa, ja niiden avulla voidaan joissain tapauksissa tarkastella myös politiikkojen vaikutuksia toimialaan. Kukin päätösmalli on esitetty ajatellen myöhempää julkaisua referoidussa sarjajulkaisussa.

Väitöskirjan menetelmälliset kontribuutiot tarjoavat uusia näkökulmia tarkasteltaviin päätösongelmiin. Esimerkiksi metsien optimaalista hakkuuta koskevat väitöskirjan tulokset osoittavat, että riskien monitasoisella rajoittamisella useilla aikaperiodeilla ja luottamustasoilla voidaan merkittävästi vähentää riskejä ilman merkittävää odotetun tuoton vähentymistä. Sähkösopimusportfolion hallintaa tukevat tulokset osoittavat, että hinnan ja kuorman välinen korrelaatio on tärkeää mallintaa, sillä muuten riskit saatetaan arvioida liian vähäisiksi, jolloin päätökset eivät ole välttämättä optimaalisia. Voimalaitosten investointipäätöksiä koskeva malli tukee näkemystä, jonka mukaan hiilidioksidipäästöpolitiikan epävarmuudet voivat johtaa yhä keskittyneemmän ja vähemmän kilpailukykyisemmän sähkömarkkinan kehittymiseen, koska isot rahoitusasemaltaan vahvat sähköntuottajat tekevät uusia voimalaitosinvestointeja todennäköisemmin kuin uudet ja pienet projektirahoitteiset itsenäiset sähköntuottajat. Tuotekehitysprojektien reaalioptioiden arvottamista koskevat tulokset osoittavat, että reaalioptioiden arvo ei välttämättä kehity monotonisesti kilpailun kiristyessä, ja että tuotekehityksen vahvistamista sekä tuotteen markkinoinnin viivästämistä koskevat optiot ovat tyypillisesti hyödyllisimpiä, kun kilpailu on vähäistä.

Avainsanat: Päätösanalyysi, sijoituksen arviointi, stokastinen optimointi, portfolio-optimointi, reaalioptiot, riskienhallinta, skenaarioiden luonti

Academic Dissertation

Systems Analysis Laboratory

Department of Mathematics and Systems Analysis

Helsinki University of Technology

Applications of Stochastic Modeling for Investment Decision-Making under Market Uncertainties

Author:	Janne Kettunen
Supervising professor:	Professor Ahti Salo, Helsinki University of Technology, Finland
Preliminary examiners:	Professor Jussi Keppo, University of Michigan, USA
	Professor Afzal Siddiqui, University College London, United Kingdom
Official opponent:	Professor Benjamin Hobbs, Johns Hopkins University, USA

Contributions of the Author

Janne Kettunen is exclusively responsible for writing this dissertation. He has also implemented all the required computational tools as well as conducted and analyzed the experiments using these tools. His understanding of the different problem contexts and the development of his modeling skills have benefited from interactions with several people.

In chapter 2, discussions with Professor Ahti Salo guided the author in the formulation of risk constraints. Furthermore, phone conversations with Dr. Mikko Kurttila helped the author obtain a better understanding of the problem of harvesting forest stands.

In chapter 3, the author's problem formulation of the two correlated uncertainties benefited from discussions with Professors Ahti Salo and Derek Bunn. The author also received advice from Professor Derek Bunn for estimating the model parameters from time series data.

In chapter 4, the author obtained guidance from Professor Derek Bunn and Dr. William Blyth who helped him understand how carbon policies impact firm-level decisions. Besides, the comments of the judges of the "Dennis J. O'Brien United States Association for Energy Economics Best Student Paper Competition" have been useful in shaping this chapter.

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Calgary, October 2009

Janne Kettunen

Abbreviations and Acronyms

VAR	value-at-risk
CVAR	conditional-value-at-risk
CFAR	cash-flow-at-risk
CCFAR	conditional-cash-flow-at-risk
GARCH	generalized autoregressive conditional heteroskedasticity
CCS	carbon capture and storage
E[NPV]	expected net present value
ROCE	return on capital expenditure
NPD	new product development
WTA	winner-takes-all
CI	competition intensity
CC	competitors' capability

Contents

Chapter 1
Introduction

1.1. Concerns in Investment Decision-Making

Profit-seeking organizations make investment decisions with financial implications under uncertainty about returns. These returns can be uncertain due to multiple market sources, such as the cost of raw materials, variable demand levels, or existing competing products. Moreover, investment decisions may involve managerial flexibilities, or real options (Trigeorgis 1996), which can allow, for example, postponing the investment to obtain more information or upgrading the facility later on to improve its efficiency. Further, organizations may have to consider the portfolio of assets that can be invested in when they seek to hedge risks. In this setting, this dissertation focuses on analysis of an investment decision-making and its financial implications under market uncertainties while acknowledging risks and real options. Models in support of these decisions represent a methodologically challenging and practically relevant research field combining decision analysis, stochastic modeling, and financial modeling.

Several approaches have been developed to support investment decision analysis. The conventional approach is to calculate the net present value of the investment by discounting the expected cash flows as presented in corporate finance (Brealey et al. 2008). However, conventional net present value calculations do not account for managerial flexibilities that allow an investor to adjust the course of the investment (e.g., Dixit and Pindyck 1994). For the valuation of managerial flexibilities, analytical solutions based on the Black and Scholes (1973) model have been proposed. However, these analytical solutions cannot always be readily applied because they rely on restrictive assumptions that do not necessarily hold: For instance, it is assumed that (i) exercising the flexibility may be possible only at a certain pre-specified point in time, (ii) there exists only one source of uncertainty, (iii) variance of the uncertainty is constant, and (iv) the exercise price of the real option is known before hand and is constant. Beyond the Black and Scholes (1973) model there are extensions, which overcome some of these assumptions but not all of them concurrently. These include the extension to perpetual options (Dixit and Pindyck 1994), the consideration of two sources of uncertainty (Pindyck 2002, Adkins and Paxson 2008), the accommodation of stochastic volatility (Benhassine 2006), and the modeling of uncertain investment cost (Dixit and Pindyck 1994). To relax all of the assumptions concurrently, numerical methods have been developed, such as Monte-Carlo simulations (e.g., Rubinstein and Kroese 2007, Vehviläinen and Keppo 2003). The least-squares Monte Carlo simulations (Longstaff and Schwartz 2001) can be applied to price even American-style (real) options. But in most cases, Monte Carlo simulation based methods do not properly reflect the flow of information in the investment decision-making, particularly if the optimization is done over each simulation trial independently.

The stochastic dynamic programming approach (e.g., Huchzermeier and Loch 2001, Reinelt and Keith 2007) helps overcome this problem as it can reflect the flow of information in the investment decision-making. It is based on backward induction and recursive optimization over a scenario tree that represents uncertainties. Thus, a crucial part of the problem formulation is the generation of the scenario tree. This is typically done via a lattice that is a discrete time and state approximation of the underlying stochastic processes. While the dynamic stochastic programming approach is suitable for many investment valuation and appraisal contexts, it is neither flexible enough to accommodate constraints for cash-flow positions during intermediate periods, nor can it easily account for dependencies among decisions in which future decisions depend on past decisions.

Stochastic programming approaches (e.g., Birge and Louveaux 1997) do not have these limitations because they are based on mathematical programming in which constraints can be set in any time periods and can be used to link dependencies between past and future decisions. In stochastic programming approaches, uncertainties are modeled using a scenario tree as in stochastic dynamic programming thought the scenario generation can be more complex than in stochastic programming approaches (e.g., Høyland and Wallace 2001, Gröwe-Kuska et al. 2003). An additional part of the problem formulation in stochastic programming approaches is the specification of the nonanticipativity constraints which ensure that decisions are taken without knowing in advance the future outcomes. While stochastic programming approaches are more intensive computationally, improvements in computational capabilities have made them tractable and applicable even in large scale problems (e.g., Sen et al. 2006).

This dissertation develops scenario-based decision models in support of investment decision-making and analysis under market uncertainties by applying stochastic programming and dynamic stochastic programming in several application contexts, such as the optimal harvesting of forest stands, the management of electricity contract portfolios, the investments in power plants, and the valuation of real options in new product development. The applications demonstrate the feasibility of scenario-based modeling approaches, among others when

- the management of risks is conducted in multiple time periods,
- there exist several correlated uncertainties,
- investors are heterogeneous in their risk aversion, for example, and
- there are several actors, who interact in competitive markets.

1.2. Methodological Background

In scenario-based investment modeling, regardless of the application context, it is important to consider the following five modeling components: (i) the formulation of the objective function, (ii) the generation of scenarios that represent the uncertainties, (iii) the measurement and management of risks, (iv) the representation of managerial flexibilities, and (v) the portfolio of investment opportunities. As shall be argued, these modeling components need to be considered concurrently as they are interdependent. For instance, decision objectives may call for the measurement of risks, risks depend on the overall portfolio and can be measured if the uncertainties are modeled, and uncertainties influence the value and use of managerial flexibilities.

1.2.1. Formulation of Objective Function

The objective function can be formulated in alternative ways, among others: (i) maximizing the expected value of the investment subject to risk constraints (Eppen et al. 1989), (ii) minimizing risks subject to constraints on the expected return, (iii) maximizing the expected value of the investment from which is subtracted a risk term (Yu 1985), and (iv) maximizing the probability of achieving a return over a target level subject to constraint on the expected return (Brown and Sim 2009). The first approach is prevalent in practice, because many companies, particularly in the financial sector, seek to maximize the profitability of the investment subject to regulatory constraints on risk (e.g., Sharpe 2002).

1.2.2. Modeling of Uncertainties

The generation of scenarios that represent the uncertainties can be approached in different ways. To begin with one approach is to generate scenarios based on decision analytic methods that rely on the subjective estimations of experts (e.g., Keeney and von Winterfeldt 1991). Thus, scenario analysis makes it possible to analyze long-term future uncertainties that are inherently different from those that are considered relevant today. Further, scenario analysis based on experts' opinions can represent non-traditional stochastic processes and risk factors, such as political, operational, model, and liquidity risks. If, however, there are reasons to believe that historical data may characterize future developments of uncertainties, then it is appealing to consider methods that are based on data, for example, by deriving the parameters for scenario generation to match the moments or other statistical properties of data (e.g., Casey and Sen 2005, Pennanen 2005, Høyland and Wallace 2001, Smith 1993, Gülpinar et al. 2004). These approaches include the following scenario generation methods: (i) simulating scenarios from their distributions, (ii) selecting scenarios by solving optimization problems, which satisfy the stated conditions, and (iii) using a hybrid of these two approaches.

Alternatively, scenarios can be generated by discretizing the underlying stochastic process as is commonly done in the discrete time scenario approaches of the finance literature. Such approaches can approximate the stochastic process of a single uncertainty using, for example, the recombining binomial tree model of Cox et al. (1979). Their model provides an arbitrage-free pricing environment by deriving risk-neutral scenario probabilities under which the scenario outcomes are discounted using the risk free rate. Similar approaches can also model multiple correlated stochastic processes of several uncertainties that can exhibit mean reversion and volatility clustering (e.g., Peterson and Stapleton 2002). These approaches have several advantages: For instance, (i) they can match the market observed prices of the financial contracts, (ii) they can provide an arbitrage free pricing environment, and (iii) their parameters can be estimated based on historical time series data.

The granularity of the generated scenarios may not be at the level of the required accuracy, particularly in the case of managing extreme risks. One approach is to apply the importance sampling method (e.g., Infanger 1993). The principle in importance sampling is to generate scenarios that relate to a certain percentile of the probability distributions in order to capture more accurately extreme outcomes, for example. Another approach is to increase the number of branches, though this may result in the loss of computational tractability.

Methods for reducing the number of scenarios have been developed for problems that would be otherwise intractable (e.g., Dupacova et al. 2003, Gröwe-Kuska et al. 2003, Heitsch and Römisch 2003). These methods rely on algorithms that seek to reduce the number of scenarios so that the remaining scenarios approximate the original problem in terms of chosen probabilistic measures such as mean or higher moments.

The appropriateness of the scenario generation method depends on the application context (Høyland and Wallace 2001). If, for example, the problem deals with financial portfolio optimization or financial contracts, then a requirement for the generated scenarios is that they provide an arbitrage free pricing environment (e.g., Klaassen 2002).

1.2.3. Measurement of Risk and Characterization of Risk Aversion

In the classic mean-variance model (Markowitz 1952), risk aversion can be modeled by setting constraints for the standard deviation or variance. However, because variance and the standard deviation penalize upside potential as well, other risk measures have been suggested. These include measures such as (i) the lower semi-absolute deviation (Konno and Yamazaki 1991, Ogryczak and Ruszczynski 1999), which measures the expected shortfall of the terminal cash position relative to the expectation and (ii) the expected downside risk (Eppen et al. 1989), which measures the downside deviation relative to a pre-specified target level.

Alternatively, risk aversion can be based on the expected utility theory (von Neumann and Morgenstern 1947) where the returns are mapped to a utility level using utility functions that are strictly increasing and concave for risk-averse investors (e.g., Delquie 2008). In decision analysis, risk aversion using utility functions is often combined with decision trees and dynamic stochastic programming (e.g., Keeney and von Winterfeldt 1991, Smith and Nau 1995, Smith and Mccardle 1998).

Yet, extreme risks are often of the greatest concern to decision makers. To model the aversion of the extreme risks, constraints can be set for the value-at-risk (VAR) risk measure, which quantifies the maximum amount of money that may be lost over a certain period of time, with a certain level of confidence. While VAR is the de facto standard of the financial industry (e.g., RiskMetrics Group 2009), it has been criticized (e.g., Embrechts et al. 1999, Alexander and Baptista 2002, Szegö 2002) because it is not a coherent measure, i.e., it fails to fulfill the subadditivity requirement (Delbaen 2000) with the result that diversification may increase VAR. Due to this deficiency, an alternative risk measure Conditional-VAR (CVAR; e.g., Uryasev 2000, Rockafeller and Uryasev 2000, Artzner et al. 1999) has been proposed, which measures the expected loss with a confidence level $\beta \in [0, 1)$, conditional on the occurrence of the tail event $1 - \beta$. CVAR is a coherent and a convex risk measure and hence suitable for linear optimization problems. In practice, companies seem to use risk constraints that are set within their financial planning models for investment in terms of cash flows, such as cash-flow-at-risk, which is a cash-flow based version of VAR (Froot et al. 1993, Denton et al. 2003, Minton and Schrand 1999, LaGattuta et al. 2001).

1.2.4. Representation of Real Options

Real options offer managerial flexibility, whose value can be significant enough so that it needs to be explicitly included in the investment valuation (Mittendorf 2004, Tseng and Barz 2002, Meier et al. 2001). The five most commonly cited managerial flexibilities are decisions to (i) abandon, (ii) defer, (iii) expand, (iv) contract, and (v) switch the operating mode of investments (Trigeorgis 1996). An investment opportunity can constitute even a set or a sequence of real options as presented by Grenadier and Weiss (1997).

The value of managerial flexibilities is fundamentally driven by uncertainties. However, as Huchzermeier and Loch (2001) and Santiago and Vakili (2005) demonstrate, an increase in an uncertainty does not necessarily increase the value of managerial flexibilities. Furthermore, Smit and Trigeorgis (2004) highlight the importance of considering competition when managerial flexibilities in R&D projects are evaluated. They suggest, among others, that the value of a managerial flexibility to delay a product's launch may be eliminated by competition.

The valuation of an investment with managerial flexibilities requires a holistic approach in which the project and its embedded managerial flexibilities are valued together. Holistic approach is essential because the value of the managerial flexibilities is not necessarily additive (Trigeorgis 1993).

1.2.5. Portfolio of Investments

Problems where it is possible to invest in multiple assets are complicated by the following aspects, among others. First, the risk of the portfolio of investments is not, in general, the sum of the risks of the individual investments because investments can be correlated, such that they hedge each other's risks thereby reducing the risk of the portfolio (Markowitz 1952). Furthermore, the available resources may prevent investments in all desirable opportunities resulting in an optimal portfolio selection problem. Such resource-constrained portfolio problems can be particularly challenging when the investment decisions are of the "no go /go" type resulting in a knapsack optimization problem.

For resource-constrained portfolio problems, Gustafsson and Salo (2005), for instance, propose a modeling framework that is based on multiple overlaid decision trees and applies stochastic optimization over the scenarios maximizing the expected value of the portfolio. If the portfolio value is measured using several attributes and their weighting information is incomplete the decision support model of Liesiö et al. (2007) can be applied. This method is based on the computation and analysis of all non-dominated portfolios.

1.3. Approach of Dissertation and Key Managerial Questions

To validate the feasibility of the scenario-based modeling approach and its benefits, it is pertinent to apply scenario-based modeling in a wide range of investment decision contexts. These decision contexts should be representative enough to draw general conclusions regarding the approach. In particular, the following four perspectives are considered when selecting the application contexts.

First, the selected application contexts need to reflect how risks can be managed at multiple levels, e.g., several time periods and confidence levels concurrently. Risk management in multiple concurrent time periods is needed, for example in the financial sector because risks need to be curtailed consistently below a pre-specified level due to regulatory reasons (US Department of the Treasury 2007, Keppo et al. 2009). Further, multiple level risk management may be needed if a firm is close to financial distress or if the planning horizon is long as in the case of a nuclear power plant whose investment is evaluated over its entire operating time.

Second, the selected application contexts should include investment decision-making with multiple correlated uncertainties. Investment decisions often have several correlated uncertainties, for example if the investment deals with a facility that provides services or goods, whose demand and price are uncertain. One approach to accommodate this is to use revenue as a numéraire to represent the impact of both uncertainties. This approach can be computationally less intensive. However, when the value of the investment depends on how the operations are managed, this approach may not be suitable, because it does not provide information about the demand and price levels, which may be needed in the management of operations. Hence, the explicit representation of multiple correlated uncertainties can be helpful even if it is computationally more intensive, because the number of scenarios increases exponentially in the number of uncertainties and time periods. Besides evaluating the computational tractability of the scenario-based approach when including explicitly multiple correlated uncertainties, it is also important to assess the need to model the correlations themselves.

Third, the application contexts should be selected to reflect the feasibility of the scenario-based modeling approach in incorporating the heterogeneity of investors. Investors can be heterogeneous, among others, in terms of the level of risk aversion, the financial conditions, and the existing asset portfolio. The representation of investor heterogeneity is beneficial, for example when the impacts of different Government policies for different types of investors are analyzed and how these policies may influence the evolution of the industry as a whole.

Fourth, it is relevant to consider application contexts in which competition is present, as is the case in industries that develop new products. Besides the challenge to model and represent the different levels of the competition in scenario-based approach, it is also of interest to consider the impacts of the competitive environment on investment decision-making.

Chapters 2 to 5 present scenario-based decision models that covers the previously stated four perspectives. These decision models are developed for (i) the optimal harvesting of forest stands, chapter 2, (ii) the management of electricity contract portfolios, chapter 3, (iii) the investments in power plants, chapter 4, and (iv) the valuation of real options in new product development, chapter 5. Altogether they demonstrate the possibilities of the scenario-based decision modeling approach. These decision models build on the same methodologies and they have been presented in view of later publication in refereed journals.

More specifically, chapter 2 considers the problem of a forest owner who needs to plan harvesting strategies under the timber price uncertainty. In particular, it analyzes the efficiency of risk management and the implications of applying risk constraints both at the intermediate and the terminal time periods concurrently compared with the case of applying only a terminal CVAR constraint. This is because managing risks only in the terminal time period is not enough if risks are needed to be managed consistently due to the forest owner's being close to financial distress or needing regularly a pre-specified cash flow to cover other financial liabilities, for example. Chapter 2 seeks to answer to the key managerial questions: **How can a forest owner manage risks of the forest stand portfolio efficiently? What are the implications of applying several risk constraints concurrently?**

Chapter 3 considers the decision problem of an electricity retailer who needs to deliver an uncertain supply of electricity by purchasing it at uncertain price from the spot market and when it can also purchase future contracts to hedge the risks. The problem is further complicated as the stochastic processes of the electricity load and spot price are correlated and exhibit volatility clustering and mean reversion. This developed model captures (i) the correlation between spot price and load, (ii) premiums on future contracts, and (iii) temporal risk preferences at intermediate time periods over the contracting horizon. Chapter 3 answers the following key managerial question: **What are the main drivers of the risks faced by electricity retailers with different risk preferences under price and demand uncertainties?**

Chapter 4 analyzes the long-term investment decision-making of a power utility that is considering to invest either in a new nuclear, coal, or gas power plant. The underlying uncertainty is the climate change policy that is manifested in the uncertain carbon price influencing hence the profitability of the power plant investment. Within this context is considered how the investment decision differs by companies that are heterogenous in terms of their risk aversion, existing asset portfolio, cost of capital, and opportunity rate of return. Chapter 4 answers the key managerial question: **How does climate policy risk influence investment behavior and market structure in the electricity sector?**

Chapter 5 investigates the value of a new product development project and its embedded managerial flexibilities under uncertainties about competition. More specifically, the analyzed managerial flexibilities are the decision to enhance product development, the decision to abandonment development, and the decision to delay the launch of the developed product. Chapter 5 answers the following key question: **How does competition affect the value of real options and their interactions in new product development?**

1.4. Summary of Main Findings

Table 1.1 summarizes the key results of this dissertation. In particular, it provides brief answers for the research questions that are presented in the previous section and describes the methodological contributions of chapters 2-5.

Table 1.1 Main contributions

Chapter	Key research questions	Methodological contributions	Essential findings
2	How can a forest owner manage risks of the forest stand portfolio efficiently? What are the implications of applying several risk constraints concurrently?	Introduces a multi level risk management in the forest portfolio optimization.	The reduction of extreme risks is initially efficient, in terms of reducing significant amount of risk with small decrease in the expected terminal wealth, but as more risk is reduced the less efficient it becomes. The introduction of risk constraints at several time periods allows forest owners to curtail risks according to their preferences.
3	What are the main drivers of the risks faced by electricity retailers with different risk preferences under price and demand uncertainties?	Develops a framework for dynamic portfolio analysis that accounts for correlated uncertainties.	Risk-averse electricity retailers are most susceptible to the drivers of forward risk premiums, while competitive electricity retailers to the price related uncertainties.
4	How does climate policy risk influence investment behavior and market structure in the electricity sector?	Extends the analysis of investment decisions to account for heterogeneous firms.	Carbon policy uncertainty leads to more concentrated and less competitive markets.
5	How does competition affect the value of real options and their interactions in new product development?	Includes the competitive environment in investment analysis.	The value of real options may not increase monotonically with increasing competition. The competition affects whether options are complements or substitutes.

Chapter 2
Optimal Natural Resources Extraction: Application to Harvesting of Forest Stands

Chapter Summary

In the management of portfolio of forest stands, traditional profit maximization and mean-variance analysis approaches do not account for the extreme market risks that may be of considerable concern to the forest owner. This chapter develops a multistage stochastic optimization model from the point of view of a forest owner who needs to plan harvesting strategies under the price uncertainty, whereby risks are curtailed by applying risk measures, most notably conditional value at risk and satisficing risk measures. The results of the computational experiments with realistic data suggest that extreme risks can be significantly reduced without appreciable losses in the expected terminal wealth. Further, they show that specifying risk constraints on several time periods and confidence levels makes possible to curtail risks throughout the planning horizon, which offers possibilities for modeling the forest owner's temporal risk preferences. Also, the results indicate that risk-neutral forest owners harvest their forests later than risk-averse forest owners. This is because risk-averse forest owners do not want to be left with a large amount of timber at potentially low prices, which is why they harvest sooner than risk-neutral owners.

2.1. Characteristics of Natural Resources Extraction

Firms in forest, mining, or petroleum industries encounter resources management problems where they have to develop strategies for the timing of their natural resources extraction. Common to natural resource portfolio optimization is that (i) the extraction decisions are irreversible and (ii) the price of the extracted commodity is uncertain. As a result, the timing of the commodity extraction can influence profits significantly. The traditional profit maximization approach for optimizing the timing of the commodity extraction is, however, not sufficient, because it does not account for risks and, in particular, the extreme market risks, which are often of the greatest concern to decision makers. The management of these risks may also be a regulatory requirement (US Department of the Treasury 2007, Keppo et al. 2009). As a realistic example of a portfolio optimization problem in the management of natural resources, we consider the harvesting problem of a forest stand portfolio in which the growth of forest stands should also be accounted for (Hyytiäinen and Penttinen 2008). The central modeling challenge is to formulate the forest portfolio optimization problem whilst curtailing the extreme market risks, due to changes in the timber price, according to the risk preferences of the forest owner.

The management of the extraction strategy of an individual natural resource has been considered, for example in mining (e.g., Kamrad and Ernst 2001) and forestry (e.g., Brazee and Mendelsohn 1988, Gong 1994). At the portfolio level, forestry publications concern mainly the evaluation of the portfolio of forest lands (e.g., Mills and Hoover 1982, Thomson 1991) or portfolio of asset classes in which a forest stand is one choice (e.g., Thomson 1997, Heikkinen and Kanto 2000).

Such portfolio approaches do not, however, consider harvesting decisions that is the focus of this chapter. Among the papers that consider forest stand harvesting decisions, one approach for risk management has been to use the mean-variance approach of Markowitz (1952). Reeves and Haight (2000) as well as Hyytiäinen and Penttinen (2008), for example, use such approach. Alternatively, the management of risks has been suggested using a negative exponential utility function (Heikkinen 2003). However, more recent approaches to risk management, such as conditional-value-at-risk (CVAR) (e.g., Rockafeller and Uryasev 2000, Uryasev 2000) and satisficing risk measures (Brown and Sim 2009), have not been applied in the forest portfolio optimization.

The main contribution of this chapter lies in applying these new risk management approaches to curtail the risk of a forest owner. In particular, we analyze the effects of using several risk constraints concurrently. To our knowledge, this is the first approach of this kind and seeks to fill the existing gap in the literature in the forest portfolio optimization and, more generally, in the natural resources portfolio management.

Particularly, we develop a multi-stage stochastic optimization model (e.g., Birge and Louveaux 1997) for determining the optimal harvesting policies for a forest portfolio owner who owns a forest holding consisting of several forest stands. Each forest stand has its unique growth rate, which is accounted for through a growth model. The harvesting decisions need to be taken in the presence of an uncertain timber price that is modeled through a scenario tree. Consequently, the market risks of the forest owner constitute of scenarios with low timber prices.

Extreme market risks can be curtailed using the value-at-risk (VAR) measure, which is the de facto standard in the financial industry and measures losses at a pre-specified probability level (e.g., RiskMetrics Group 2009). But since VAR may not fully capture diversification benefits (e.g., Szegö 2002, Alexander and Baptista 2002, Embrechts et al. 1999) that stem from exploiting hedging opportunities due to correlations among the assets, we focus on CVAR (Uryasev 2000, Rockafeller and Uryasev 2000), which properly accounts for the diversification benefits. In short, CVAR refers to the expected tail loss beyond a pre-specified probability level. Also, since we work with cash flows, we use conditional-cash-flow-at-risk (CCFAR), which is defined in the same way as CVAR except that CCFAR refers to cash flows rather than market valuations of financial assets.

Furthermore, we apply the satisficing risk measure (Brown and Sim 2009) where the aim is to maximize the probability that the return will exceed a pre-specified threshold level subject to constraints on the expected return. This satisficing risk measure may be more intuitive than CCFAR, because it does not require the specification of a probability level.

We performed computational experiments using a realistic model with representative number of forest stands and price scenarios[1] and the results of the experiments suggest the following four insights. First, extreme risks can be significantly reduced without appreciable losses in the expected terminal wealth. Second, by specifying risk constraints at several time periods and confidence levels it is possible to curtail risks throughout the planning

[1] Data obtained from the Finnish Forest Research Institute

horizon modeling thus the temporal risk preferences of the forest owner. Third, risk-neutral forest owners harvest their forests later than risk-averse forest owners. This is because, by letting the forests grow further, the harvestable amount and expected terminal wealth increase with the risk of lower timber prices. Fourth, a forest portfolio formulation using satisficing risk measures can help illustrate the revenue distribution and better understand risks.

The rest of this chapter is structured as follows. Section 2.2 discusses approaches to the risk management in the forest stand portfolio problems. Section 2.3 formulates the forest portfolio model and section 2.4 presents results from computational examples. Section 2.5 considers the extensions of the approach, and section 2.6 concludes.

2.2. Risk Management in Harvesting of Forest Stand Portfolio

In an early approach that considers risk-return tradeoff in forest portfolio investments, Redmond and Cubbage (1988) apply the capital asset pricing model (CAPM) (e.g., Brealey et al. 2008) and empirically estimate the beta of a timber asset. They find that the beta of a forest investment is negative, suggesting that forest investments are counter-cyclical and diversify the risks of a stock portfolio. However, their models were statistically mostly non-significant, so that this conclusion is not very reliable. A further limitation is that their approach does not account for the decisions regarding when to harvest the forest stands.

The mean-variance portfolio optimization approach of Markowitz (1952) has also been applied to forest portfolio optimization. Hyytiäinen and Penttinen (2008) apply it to a setting in which the portfolio consists of forests and financial assets. They estimate the expected returns, variances, and covariances based on historical time series data and investigate how the optimal mix of forests and financial assets changes as a function of the risk free rate. Further, they show that the optimal amount of harvesting declines when the proportion of initial non-forest wealth is greater. We extend their approach to multiple time states and capture path dependencies in the decision-making using scenarios that represent uncertainties explicitly. Further, we consider extreme risks rather than variance, because variance also penalizes for the upside potential.

Similar to Hyytiäinen and Penttinen (2008), Reeves and Haight (2000) apply Markowitz's single state mean-variance portfolio optimization approach. They consider when and what proportions of a forest should be harvested, assuming that the forest is of uniform age and grows at a homogenous rate, and that possible harvesting times for the forest are at the ages of 20, 25, 30, 35, and 40. They provide support for risk management by applying chance-constraints in which the expected return is maximized while the return at a certain quantile is constrained to exceed a pre-specified level similar to VAR. Their model is, however, static in that all future harvesting decisions are made at $t = 0$ instead of waiting and learning from the evolution of timber prices. In contrast, we propose a dynamic multi-period model. We also relax the assumption that the forest is of uniform age and grows at a homogenous rate and allow forest stands to have different growth rates and amounts.

Heikkinen (2003) develops a stochastic program where a forest owner considers harvesting policies in a multi-period setting. In his approach, the degree of the risk aversion is modeled with a negative exponential utility function. We extend this approach further by considering additional risk measures, such as CCFAR and the satisficing risk measure. Moreover, we analyze how the risk aversion of the forest owner influences his harvesting decisions, particularly when he applies risk constraints on several time periods and confidence levels relaxing thus the assumption of having a risk neutral forest owner (Alvarez and Koskela 2007).

2.3. Decision Model for Forest Portfolio

2.3.1. Representation of Price Uncertainties

We model the uncertain evolution of the price of pine pulpwood P over a finite time horizon $t = 0, ..., T$ using the geometric Brownian motion

$$dP_t = \mu P_t dt + \sigma P_t dW_t, \tag{2.1}$$

where μ is a yearly drift, σ is a yearly volatility, and dW_t is a Wiener process. The volatility and the drift parameters are estimated based on historical time series data. This stochastic process can be approximated using a binomial lattice Cox et al. (1979) and if mean-reversion is desired using the extension of Hahn and Dyer (2008), for example. These approaches provide an arbitrage-free pricing environment by deriving risk-neutral scenario probabilities under which the scenario outcomes are discounted by the risk free rate. Thus, the risk-neutral approach permits the use of the risk-free interest rate in discounting cash flows.

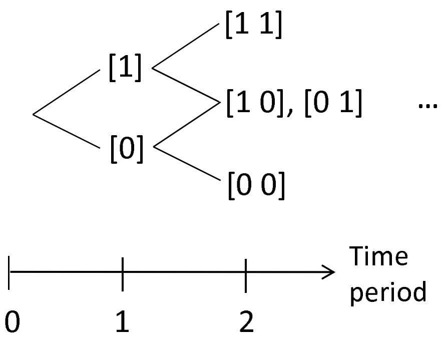


Figure 2.1 Scenario tree representation

A binomial scenario tree, consisting of 2^t scenario paths, from here on referred as scenarios, can be defined so that s^0 is the base scenario at $t = 0$ and S^t is the set of all scenarios at time t. A scenario $\mathbf{s^t}$ at time t is a row vector with t elements. The moves in the scenario tree are given by the vector element s_i^t that is 1 if the price increases, and 0 if the price decreases in the scenario tree in period $i = 1, ..., t$. Hence, the set of all scenarios is as follows

$$S^t = \{\mathbf{s^t} | s_i^t \in \{0,1\}, \quad i = 1, ..., t, t = 1, ..., T\}.$$

The unique immediate predecessor of scenario $\mathbf{s^t} \in S^t$ $(t > 0)$ is $b(\mathbf{s^t}) = \mathbf{s^{t-1}} \in S^{t-1}$ such that scenario $\mathbf{s^{t-1}}$ is the $t-1$ subvector of $\mathbf{s^t}$, in other words if $\mathbf{s^t} = [u_1\ u_2\ u_3\ ...\ u_t]$ then $b(\mathbf{s^t}) = [u_1\ u_2\ u_3\ ...\ u_{t-1}]$ (see Figure 2.1).

2.3.2. Forest Portfolio Optimization

We define the following parameters

$F \in \mathbb{Z}^+$ number of forest stands,

$x^j_{\mathbf{s^t}} \in \mathbb{R}^+$, j=1,...,F amount (m^3) of timber harvested in scenario $\mathbf{s^t} \in S^t$,

X^t set of all timber harvesting decisions until period t,

$a^j_{\mathbf{s^t}} \in \mathbb{R}^+$, j=1,...,F amount of harvestable timber (m^3) in scenario $\mathbf{s^t} \in S^t$,

$p_{\mathbf{s^t}} \in \mathbb{R}^+$ price of timber (EUR/m^3) in scenario $\mathbf{s^t} \in S^t$,

$c_{\mathbf{s^t}} \in \mathbb{R}^+$ cash position in scenario $\mathbf{s^t} \in S^t$,

$g^{jt} \in \mathbb{R}^+$, j=1,...,F, t=1,...,T expected forest growth percentage per time period,

$r \in \mathbb{R}^+$ risk free rate per time period, and

$prob_{\mathbf{s^t}}$ $\in$ [0,1] probability of occurrence of scenario $\mathbf{s^t} \in S^t$.

The optimization problem of a forest owner is

$$\max_{X^T} \left[\sum_{\mathbf{s^T} \in S^T} prob_{\mathbf{s^T}} c_{\mathbf{s^T}} \right], \tag{2.2}$$

that is maximized subject to cash position constraints, $\forall \mathbf{s^t} \in S^t$

$$c_{\mathbf{s^t}} = \begin{cases} \sum_{j=1}^{F} x^j_{\mathbf{s^t}} p_{\mathbf{s^t}} & t = 0 \\ \\ c_{b(\mathbf{s^t})}(1+r) + \sum_{j=1}^{F} x^j_{\mathbf{s^t}} p_{\mathbf{s^t}} & 0 < t \leq T, \end{cases} \tag{2.3}$$

forest growth constraints, $\forall \mathbf{s^t} \in S^t$, $j = 1, ..., F$,

$$a^j_{\mathbf{s^t}} = \begin{cases} a^j_0 & t = 0 \\ \\ (a^j_{b(\mathbf{s^t})} - x^j_{b(\mathbf{s^t})})(1 + g^{jt}) & 0 < t \leq T, \end{cases} \tag{2.4}$$

and harvesting constraints, $\forall \mathbf{s^t} \in S^t$, $j = 1, ..., F$,

$$x^j_{\mathbf{s^t}} \leq a^j_{\mathbf{s^t}}. \tag{2.5}$$

Thus, the expected terminal cash position in (2.2) is maximized subject to equation (2.3), which ensures that the cash position increases by the proceeds that are obtained from harvesting as well as from the accumulated interest. The constraint (2.4) ensures that the available amount of timber in each stand reduces by the harvested amount and increases by its growth rate. The constraint (2.5) enforces that harvesting is limited to the available amount of forest in the stand.

2.3.3. Risk Management

Conditional-Cash-Flow-at-Risk

We consider the management of risks, using a cash-flow based version of the CVAR measure (Uryasev 2000). CVAR has been previously applied to the portfolio selection of stocks (e.g., Benati 2003) and power plants (e.g., Fortin et al. 2007), among others. Figure 2.2 shows that CVAR measures the expected loss in the tail event $1-\beta$, where $\beta \in [0,1)$ is the probability of a non-tail event, also called as the confidence level. CVAR can be formulated with the help of the VAR, which defines losses at the β percentile, as follows

$$CVAR = -\mathbb{E}[return | return \leq VAR]. \tag{2.6}$$

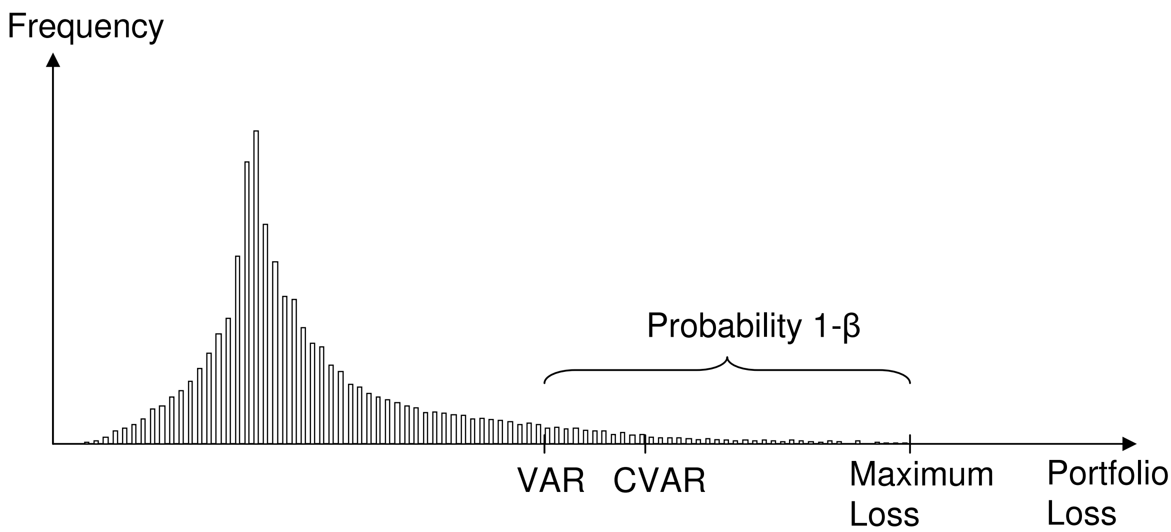


Figure 2.2 **CVAR in relation to VAR and maximum loss**

As a coherent risk measure, CVAR fulfills the following requirements when x and y are random return distributions in $\mathbb{R}$ (Delbaen 2000):

1. (Translation invariance) $CVAR(x+a) = CVAR(x) - a \quad \forall\ a \in \mathbb{R}$.
2. (Subadditivity) $CVAR(x+y) \leq CVAR(x) + CVAR(y) \quad \forall\ x, y$.
3. (Positive homogeneity) $CVAR(\lambda x) = \lambda CVAR(x) \quad \forall\ \lambda \geq 0$.
4. (Positivity) $CVAR(x) \leq 0 \quad \mathbb{P}(x \geq 0) = 1$.

More specifically, the subadditivity requirement means that the CVAR risk measure accounts for the diversification. In other words, the CVAR of asset portfolios is always less than the sum of CVARs of all assets independently.

The cash-flow based version of CVAR, CCFAR, can be presented with the help of the following parameters

$\alpha \in \mathbb{R}^+$ threshold loss level, which equals cash-flow based VAR if constraint (2.7) is active,
$R \in \mathbb{R}$ risk tolerance level measured in CCFAR, and
$\kappa_{\mathbf{s^t}} \in \mathbb{R}^+$ auxiliary variable, which measures probability weighted loss beyond cash-flow based VAR in scenario $\mathbf{s^t}$.

CCFAR can be introduced to the portfolio optimization problem at the terminal time period by augmenting constraints (2.3)-(2.5) with

$$R \geq \alpha + \frac{1}{1-\beta} \sum_{\mathbf{s^T} \in S^T} \kappa_{\mathbf{s^T}}, \tag{2.7}$$

$$\kappa_{\mathbf{s^T}} \geq prob_{\mathbf{s^T}} (-c_{\mathbf{s^T}} - \alpha). \tag{2.8}$$

The constraint (2.7) enforces that CCFAR is less than or equal to the risk tolerance level R. In (2.7) CCFAR is the sum of the threshold loss level α and the weighted average of the tail loss beyond the threshold loss level, as is specified in (2.8). If the constraint (2.7) is active, the threshold level α equals the cash-flow version of VAR (Uryasev 2000).

To curtail CCFAR risks at different confidence levels β and different time periods concurrently, it is possible to apply several CCFAR constraints. This may be required due to regulatory reasons in financial sector as the risks may need to remain below pre-specified levels consistently rather than only at the terminal period. Furthermore, multi-period CCFAR risk management may be of interest as terminal period risk management may shift some of the risks to the earlier periods. In particular, this may be not desired if the forest owner is close to financial distress and therefore has to have a strong enough cash position over the entire planning horizon.

Coherent Satisficing Risk Measure

Brown and Sim (2009) develop a coherent satisficing risk measure, which maximizes the probability of achieving a return above a threshold level $\theta \in \mathbb{R}$ such that the expected return equals a pre-specified level $\phi \in \mathbb{R}$ as follows

$$\begin{aligned} &\max \mathbb{P}\left[return \geq \theta\right] \\ &\text{subject to } \mathbb{E}[return] = \phi. \end{aligned} \tag{2.9}$$

We formulate this in the forest portfolio context by introducing $y_{\mathbf{s^T}} \in \{0,1\}$, which is an additional decision variable tracking whether terminal cash position in scenario $\mathbf{s^T}$ is greater or equal to the threshold level θ. Also, a constant δ is introduced which is a small positive constant close to 0, which ensures that the right-hand side of the constraint (2.12) remains (i) positive and below 1 if $c_{\mathbf{s^T}} < \theta$ in scenario $\mathbf{s^T}$ and (ii) greater than 1 otherwise. To implement the coherent satisficing risk measure, the objective function equation (2.2) is replaced with equation (2.10) and additional constraints (2.11)-(2.12) are included

$$\max_{X^T, y_{\mathbf{s^T}}} \left[\sum_{\mathbf{s^T} \in S^T} y_{\mathbf{s^T}} prob_{\mathbf{s^T}} \right], \tag{2.10}$$

$$\sum_{\mathbf{s^T} \in S^T} prob_{\mathbf{s^T}} c_{\mathbf{s^T}} \geq \phi, \text{ and} \tag{2.11}$$

$$y_{\mathbf{s^T}} \leq 1 + \delta(c_{\mathbf{s^T}} - \theta). \tag{2.12}$$

The constraint (2.11) enforces that the expected return has to be greater or equal to the pre-specified level ϕ and the constraint (2.12) dictates that $y_{\mathbf{s^T}}$ equals 1 if the scenario outcome is greater or equal to the threshold level θ and 0 otherwise. Note that the constraint (2.11) allows the expected terminal cash position to be also greater than ϕ, which is not the case in (2.9). This relaxation in (2.11) is needed because the exact value of ϕ may not be obtained due to the discrete scenario representation of the cash position outcomes.

2.4. Computational Results

We carried out computational experiments based on realistic data from the Finnish Forest Research Institute to explore the quantitative and qualitative implications of using CCFAR and satisficing risk measure constraints. More specifically, we illustrate the mean-CCFAR efficient frontier and compare the harvesting strategies of both risk-neutral and risk-averse forest owners based on the employment of CCFAR constraints. We compare the relative efficiency of applying several CCFAR constraints versus the application of a CCFAR constraint. Finally, we analyze the use of the satisficing risk measure and its impact on the harvesting strategies.

2.4.1. Context and Setup

The computational experiments were carried out using various specification of the forest portfolio model that is presented in section 2.3 using a ten-year planning horizon with two-year, $t = 0, 2, 4, 6, 8, 10$ periods. The scenario tree was built using the recombining binomial scenario tree of Cox et al. (1979). The branching in the scenario tree was conducted in every half year to obtain a finer grid to facilitate the management of extreme risks. Figure 2.3 illustrates each node having five child nodes in the next time state, 2 years later.

The volatility σ and drift μ of the scenario tree were estimated to be $\sigma = 12\%$ and $\mu = 0\%$ based on the stumpage price of pine pulpwood yearly time series data during 1983-2007. This time series data is illustrated in Figure 2.4. As the figure shows, the time series for the pine pulpwood price may include mean-reversion, which could be included using the approach of (Hahn and Dyer 2008), for example. The yearly risk free interest rate in the experiments is 3%.

Table 2.1 presents the forest stand portfolio that was used in the computational experiments. Specifically, each stand has a unique amount of harvestable pine pulpwood at $t = 0$ and unique expected growth rate. The expected growth rate refers to the net growth rate

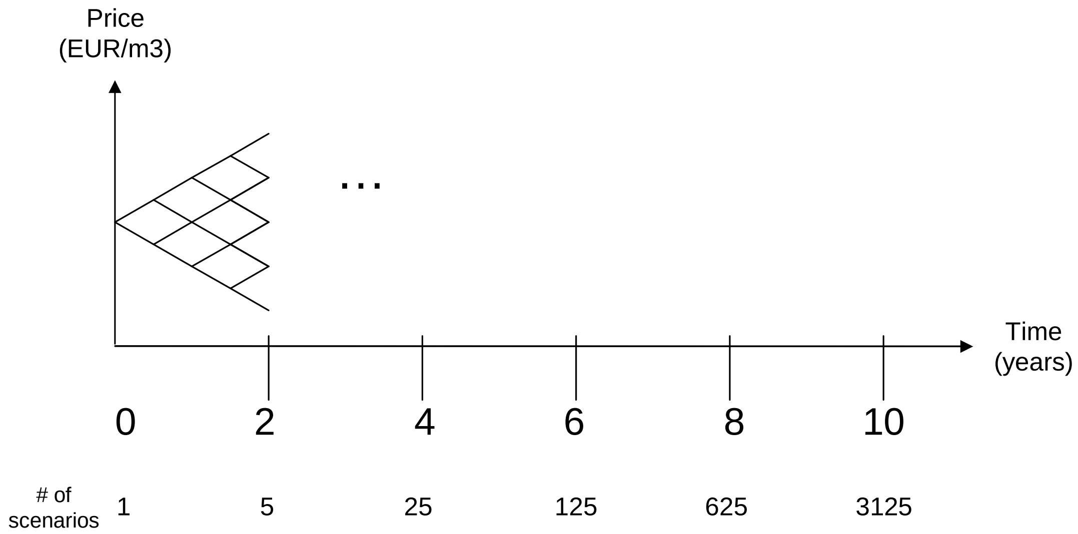


Figure 2.3 **Scenario generation**

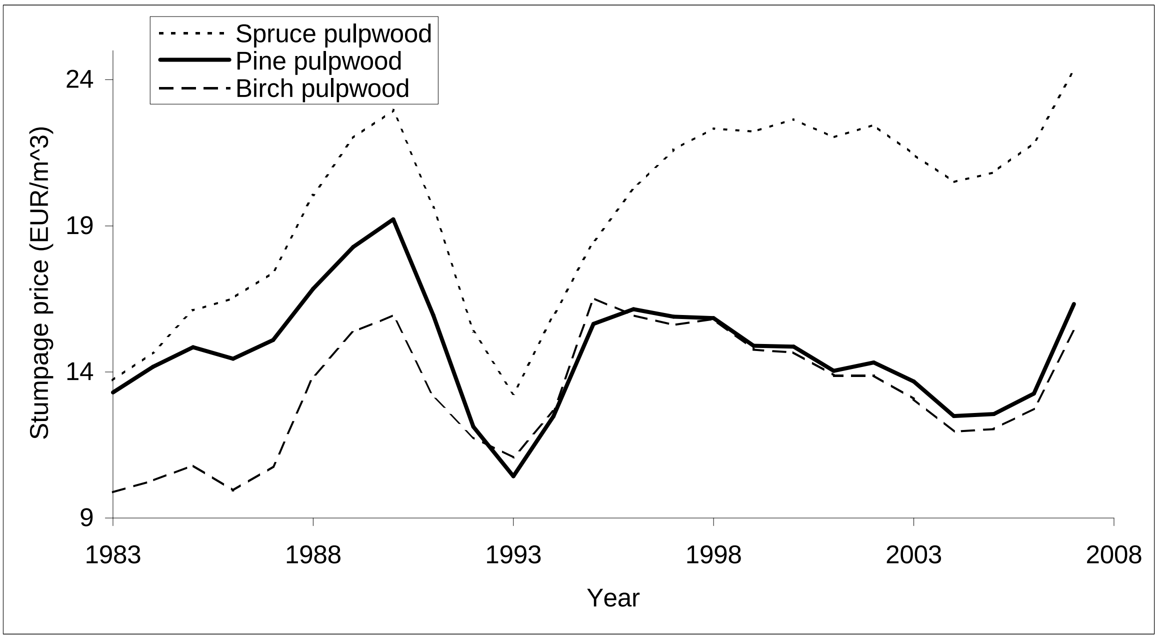


Figure 2.4 **Time series for the prices of the spruce, pine, and birch pulpwood, source: Finnish Forest Research Institute**

that also accounts for dying trees. The variability in the expected growth rates is due to different ages of the forest stands. For example, forest stand number six is young and grows quickly while forest stand two is old and grows slowly.

The forest portfolio in Table 2.1 is representative of a large private forest owner. In reality, these forest stands include pine, spruce, and birch trees and they can be used for a specific mix of pulpwood and saw log purposes. However, Figure 2.4 illustrates that the stumpage

Table 2.1 Harvestable forests data, obtained from Finnish Forest Research Institute

Stand number	Harvestable pine pulpwood at $t = 0$ (m^3)	Expected yearly growth rate (%)
1	6,884	3.9
2	6,634	1.9
3	6,421	7.6
4	5,670	1.9
5	5,385	4.6
6	4,635	19.4
7	4,477	2.7
8	4,053	14.4
9	4,031	2.1
10	4,018	19.8
11	2,325	14.3
12	2,078	14.5

The harvestable amount was multiplied by 100 to have representative forest sizes.

pulpwood price evolution of pine, spruce, and birch are similar suggesting that the obtained results and insights are representative also for forest stands with mixed tree species.

The optimization problems were solved with the Dash Optimization software Xpress®, run on a PC with 2.0 GHz Core 2 processor, 4 GB of RAM, and Windows XP operating system. The optimization models were solved in less than three minutes.

2.4.2. Risk Management Applying Single CCFAR Constraint

A forest owner can apply a CCFAR constraint to curtail its extreme market risks at time period t at the confidence level β. He may need to curtail extreme market risks due to being risk averse for extreme market outcomes or he may be close to financial distress, for example.

We applied the model in (2.2)-(2.5) and (2.7)-(2.8) when β was 95% and risk constraint was applied at the terminal time period $t = 10$. Figure 2.5 illustrates the mean-CCFAR efficient frontier. This frontier is constructed by interpolating between points obtained from a series of optimization problems where the CCFAR constraint was tightened. As 95% CCFAR measures the expected loss in the worst 5% tail event, see equation (2.6), a negative value in it represents gains.

The rightmost extreme point in Figure 2.5 corresponds to the *risk-neutral forest owner*, which maximizes the expected terminal cash position. At this point, the expected terminal cash position is about 2.49 million EUR, the risk in 95% CCFAR is -1.28 million EUR, $\alpha =$-1.37 million EUR, and the strategy is to postpone most of the harvesting until the terminal

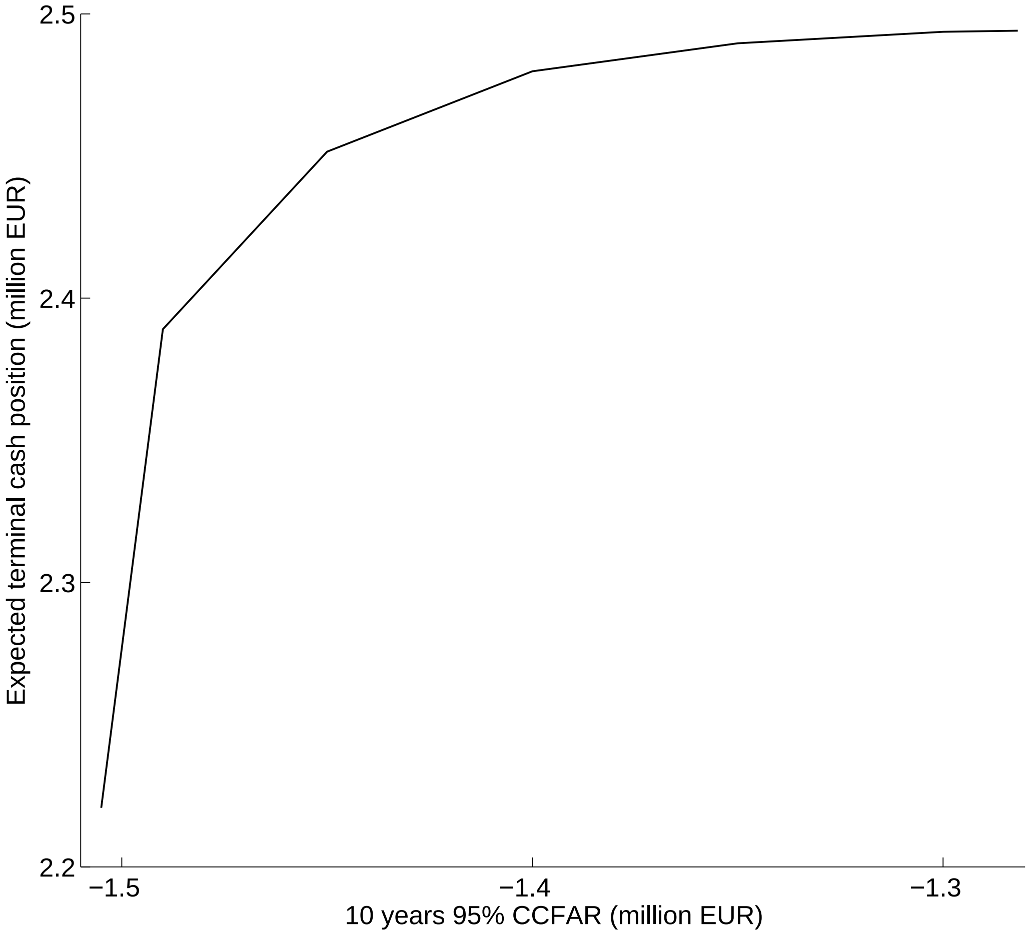


Figure 2.5 **Mean-CCFAR efficient frontier**

time period. When the CCFAR risk constraint is tightened from -1.28 million EUR the expected terminal cash position decreases as there is a risk-return tradeoff. In terms of harvesting strategy, this points to harvesting forests earlier. The leftmost extreme point in the figure we define as the *risk-averse forest owner* who minimizes the 95% CCFAR. Consequently, the horizontal difference between the left- and rightmost extreme points in the curve represents the maximum amount of risk measured in 95% CCFAR that can be reduced (in absolute terms roughly 0.2 million EUR) whilst the vertical difference between the extreme points represents the risk reduction cost (in absolute terms roughly 0.3 million EUR).

The gradient of the curve in Figure 2.5 demonstrates that reducing extreme risk is the cheapest at the rightmost extreme point but becomes more expensive the more risk is reduced. To evaluate the efficiency of risk reduction, we define a *risk reduction efficiency* as the ratio of reduced amount of risk to its cost, i.e., how many euros of 10 years 95% CCFAR risk can be reduced by the cost of one euro. The higher the risk reduction efficiency ratio the more efficient it is to reduce risk. For example, reducing risk from -1.28 million EUR to -1.4 million EUR costs roughly 0.01 million EUR =2.49 million EUR - 2.48 million EUR resulting in average efficiency ratio of $12 = (-1.28 - -1.4)/(2.49 - 2.48)$ meaning that at 10 year 95% CCFAR level extreme risk can be initially reduced by approximately 12 EUR with the cost of 1 EUR. However, the risk reduction efficiency decreases as the amount of risk being reduced increases. For example, if risks are minimized the average efficiency ratio is roughly $0.85 = (-1.28 - -1.51)/(2.49 - 2.22)$. The explanation for this phenomenon is that initially the 95% CCFAR risk can be reduced focusing on the extreme scenarios only that have a low probability of occurring. Once these low probability extreme risks are hedged, in other words forests are harvested sooner, what remains are the more probable scenarios that contribute to the 95% CCFAR risk. The cost of harvesting forests sooner is higher for these more probable scenarios. This holds when the scenarios represent a return probability distribution that is strictly decreasing in distance from the mean, as is the case for the normal distribution, for example.

Figure 2.6 illustrates the expected harvesting amounts at time $t = 0, 2, 4, 6, 8, 10$, calculated as $\sum_{i=1}^{F} x^i_{\mathbf{s^t}} prob_{\mathbf{s^t}}$, for the risk-neutral and risk-averse forest owners. Particularly, this figure demonstrates that the risk-neutral forest owner delays most of its harvesting till the terminal period as he can benefit from the forest growth. Those few forest stands that he decides to harvest at the time $t = 0$ are old, slow growing, which growth provides less expected revenues than if the forest stand is harvested and the received cash accumulates interest on risk free rate. The risk-averse forest owner, on the other hand, decides to harvest 70% of its forests initially as he can thus avoid the price risk of lower future prices. However, he also decides to let the fastest growing forests to grow as their growth helps hedge the price risk. This suggests that more risk-averse, possible non-industrial, forest owners are likely to have shorter rotation periods for their forests than the risk-neutral, perhaps industrial, forest owners. This finding is aligned with the optimization results of the studies of Hyytiäinen and Penttinen (2008), Alvarez and Koskela (2006). Sensitivity analysis with respect to the volatility of the price, i.e., +/- 50% change in volatility, shows that with a higher volatility these effects are stronger (in other words risk-averse forest owners harvest more of their forests earlier and risk-neutral forest owners postpone more of their harvesting) and with a lower volatility these effects are weaker.

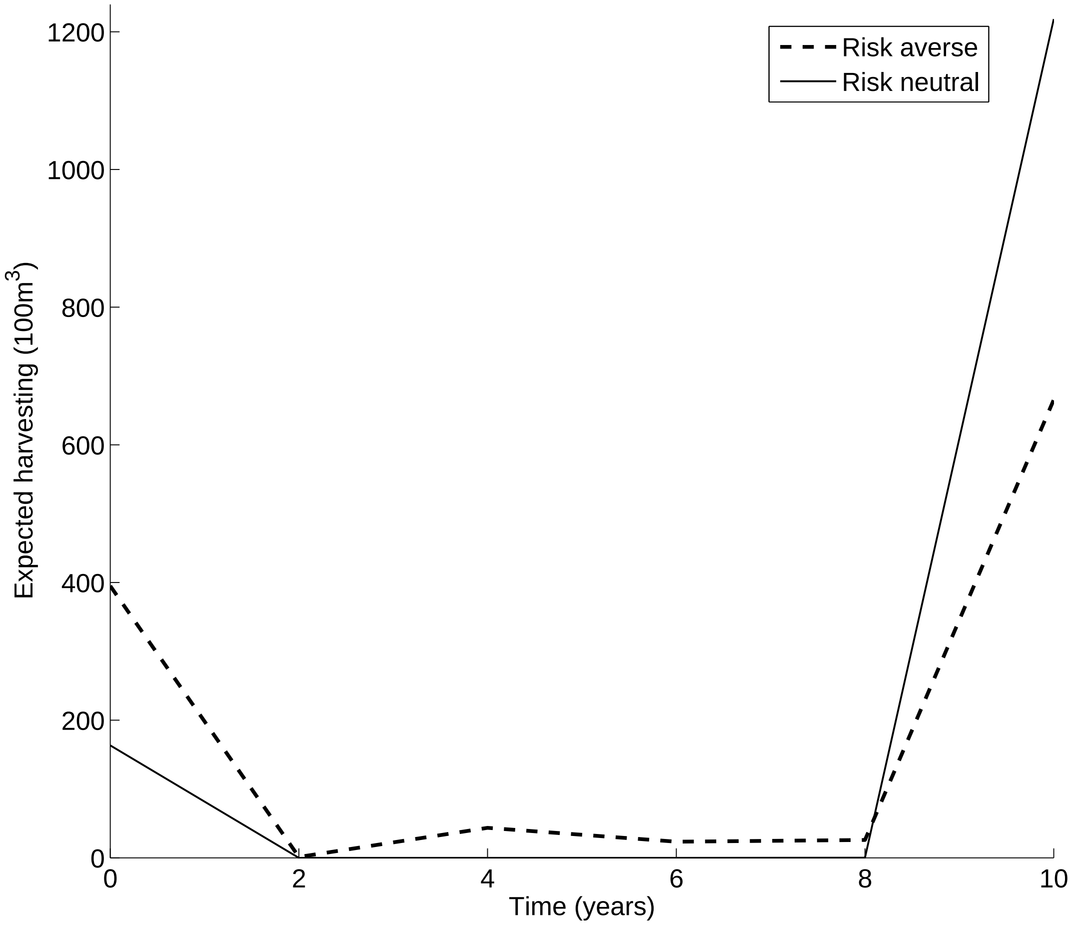


Figure 2.6 **Harvesting strategies of risk-neutral forest owner (maximizes terminal cash position) and risk-averse forest owner (minimize 10 years 95% CCFAR)**

We also scanned through the harvesting decisions of the computation results to see whether all trees or a portion of trees in the stands are harvested. The results show that harvesting is optimal to conduct stand-wise (i.e., either harvest all trees or none of the trees in the stand). This suggests that it would be possible to derive stand-specific price levels above which the stand would be harvested. However, deriving such stand-specific price levels so that they together relate to pre-specified portfolio level risks would require the development of a dedicated portfolio optimization approach in which the stand-specific price levels were the decision variables.

2.4.3. Risk Management Applying Several CCFAR Constraints

In each time period, the cash position of the forest owner can be presented using a distribution. The shape of the distribution reflects the risk and depends among others from

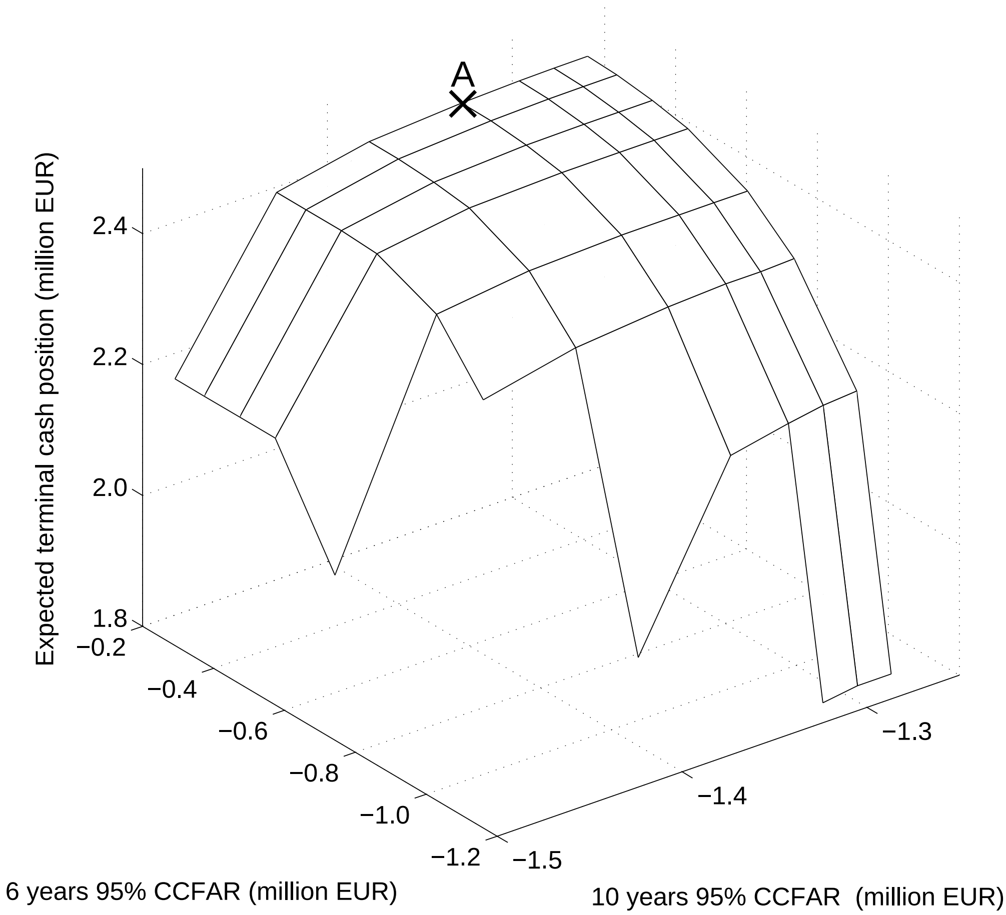


Figure 2.7 Expected terminal cash position with 6 and 10 year 95% CCFAR constraints

the pine pulpwood price process and the taken harvesting decisions. It is likely that by applying a risk constraint on one of these distributions influences not only to the shape of the distribution concerned but also those of the others. Thus, the forest owner may be interested in managing the shape of several distributions, and hence risks, in multiple time periods concurrently. In particular, this may be needed if the forest owner is close to financial distress or if he has other financial liabilities for which a pre-specified amount of cash is required regularly from harvesting. Multi-level risk management can be done, for example, by applying several CCFAR risk constraints on different time periods and percentiles, which is investigated here.

Figure 2.7 illustrates the mean-CCFAR efficient frontier when the objective function is maximized subject to 95% CCFAR constraints at the time $t = 6$ and $t = 10$. The corner point where the expected terminal period cash position is maximized yields the expected terminal cash position of about 2.5 million EUR while the 6-year and 10-year 95% CCFAR levels are about -0.32 and -1.28 million EUR, respectively. The surface is drawn by starting from this corner point and imposing increasingly tighter risk constraints.

The following four observations can be made from Figure 2.7:

1. It is not feasible to constrain both 6-year and 10-year CCFAR concurrently to their minimum levels of -1.17 and -1.51 million EUR respectively. Thus, a risk-averse forest owner who would like to minimize its risk exposure in both dimensions has to choose the relative importance of minimizing the concerning risks and set constraints accordingly.
2. The risk reduction efficiency decreases as the amount of reduced risk increases also in the 6-year CCFAR as shown by the decrease in its gradient with respect to reduced amount of risk.
3. The average risk reduction efficiency, if 6 year CCFAR risk is reduced to its minimum, is approximately $1.3 = (-0.32 - -1.17)/(2.49 - 1.83) > 0.85$ the average risk reduction efficiency of 10-year CCFAR. This suggests that the intermediate period risk can be reduced more efficiently than that of the terminal period. Intuitively, in intermediate periods, there is more scope for hedging because the risk-neutral strategy in Figure 2.6 can be adjusted to harvest some of the forests already during the intermediate periods while in terminal period risk reduction there is less room for such changes in harvesting decisions.
4. The point A is obtained by setting a single 10-year CCFAR constraint with a limit of -1.35 million EUR. At this point, the 6-year CCFAR risk is not reduced at all, still being approximately -0.32 million EUR because forests are harvested mostly in terminal period instead of harvesting also in intermediate periods, which would reduce the 6-year CCFAR.

Similarly, we explore the mean-CCFAR efficient frontier when we specify CCFAR constraints at the 95% and 99% levels at $t = 10$. Figure 2.8 illustrates this and provides the following observations:

1. It is not feasible to constrain both 95% and 99% CCFAR concurrently to their minimum levels of -1.51 and -1.39 million EUR respectively. Thus, a risk-averse forest owner who would like to minimize its risk exposure in both dimensions has to choose the relative importance of minimizing the relevant risks and set constraints accordingly.
2. The risk reduction efficiency decreases as the amount of reduced risk increases in 99% CCFAR as shown by the decrease in its gradient with respect to reduced amount of risk.
3. The average risk reduction efficiency, if the 99% CCFAR risk is reduced to its minimum, is approximately $0.66 = (-1.14 - -1.39)/(2.49 - 2.11) < 0.85$ the average risk re-

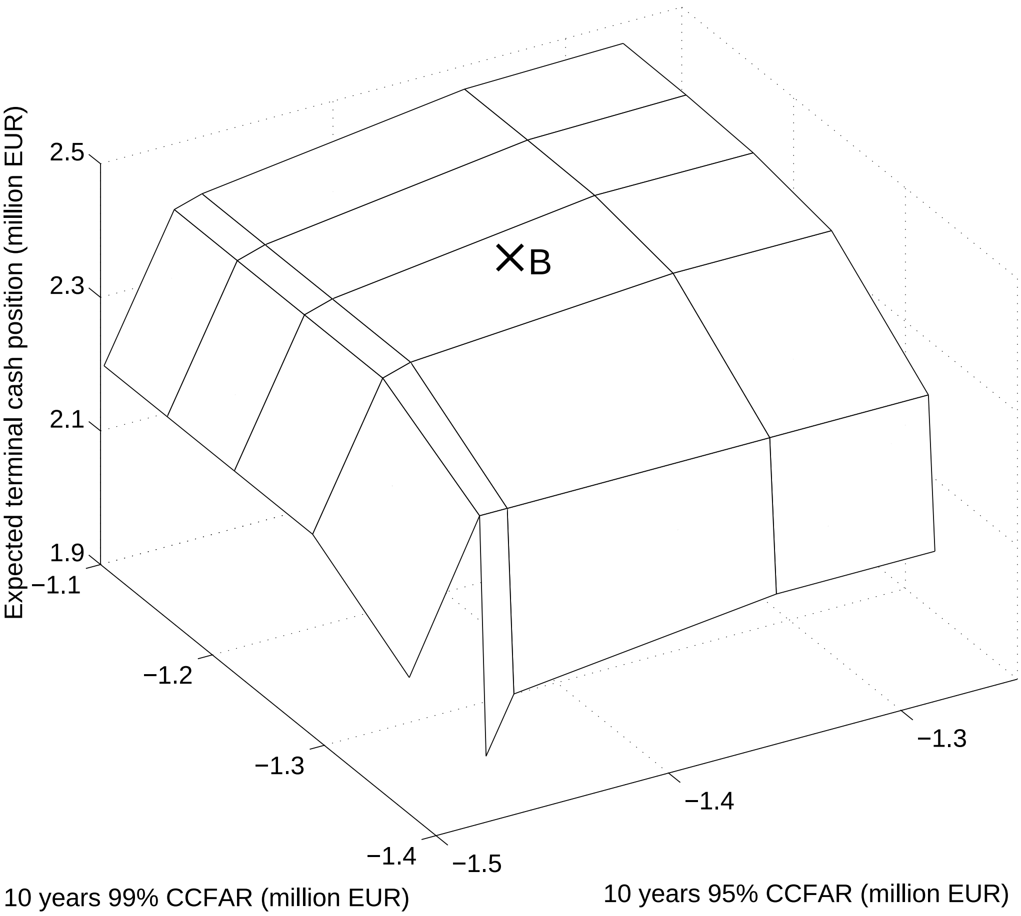


Figure 2.8 Expected terminal cash position with 95% and 99% CCFAR constraints

duction efficiency of 95% CCFAR. This suggests that the risk reduction efficiency is lower in a higher quantile of CCFAR.

4. The point B is obtained by setting a single 95% CCFAR constraint with a limit of -1.4 million EUR. At this point, the 99% CCFAR risk is approximately -1.26 million EUR. As a result, applying a CCFAR constraint at a lower confidence level may reduce risks at higher confidence levels too. Nevertheless, a forest owner may benefit by specifying risk constraints on several confidence levels as it allows to model the forest owner's risk preferences in greater detail.

2.4.4. Risk Management Using Satisficing Risk Measure

Portfolio optimization using the satisficing risk measure is a new complementary risk management approach, which can be used to evaluate the probability of achieving a desired financial position. It may be more intuitive for a forest owner than CCFAR because it

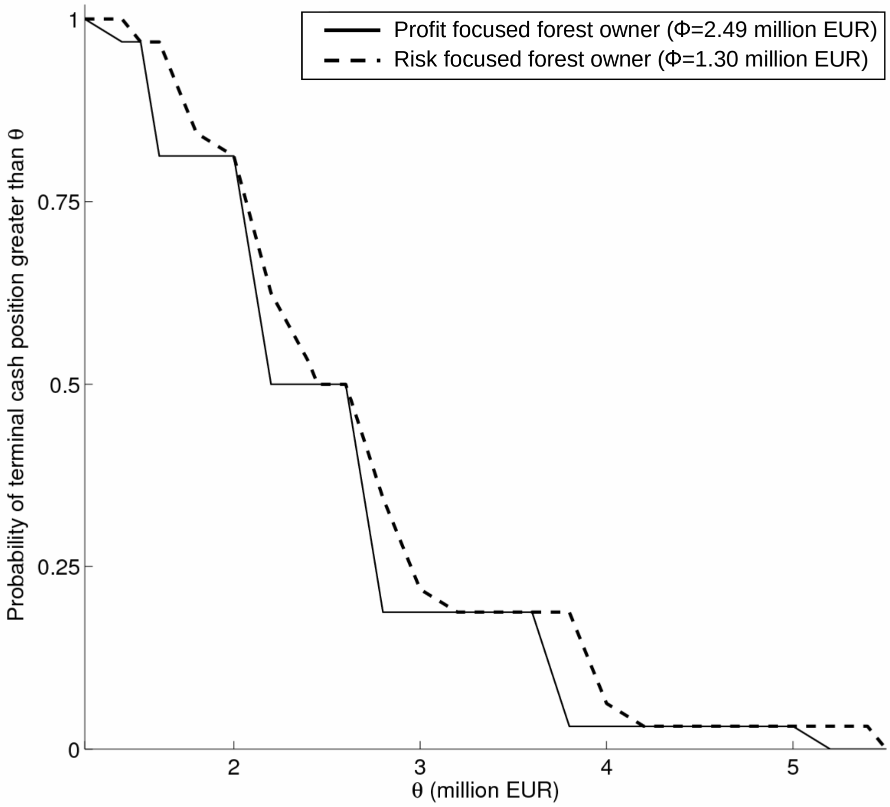


Figure 2.9 **Terminal cash position profile using satisficing risk measure**

does not require the specification of a probability level in which the risks are curtailed but instead (i) a benchmark or fixed target cash position that is needed to achieve at minimum and (ii) a threshold cash position above which the probability of achieving is maximized.

We apply a coherent satisficing risk measure, which maximizes the probability of achieving a terminal cash position that exceeds a benchmark cash position θ, equation (2.10), subject to constraints (2.3)-(2.5) and (2.11)-(2.12). Because the formulation of the satisficing risk measure is computationally more intensive, resulting in a mixed integer program, we conducted the experiments using a scenario tree in which branching is done once in a two year interval instead of every half year. In all other respects, input parameters and the applied portfolio remained the same.

Figure 2.9 illustrates the probability of the terminal cash position being greater than a benchmark cash position θ. The figure is obtained by optimizing at increasing values of θ when the required expected terminal cash position levels ϕ are (i) 2.49 million EUR, which is the maximum achievable expected terminal cash position in our satisficing risk measure optimization problem and (ii) 1.30 million EUR, which is the minimum expected terminal cash position in our satisficing risk measure optimization problem. When ϕ is 2.49

million EUR it characterizes a *profit-focused forest owner* and when ϕ is 1.30 million EUR it characterizes a *risk-focused forest owner.* As Figure 2.9 shows, the profit-focused forest owner has always a lower or equal probability of achieving the benchmark cash position θ than the risk-focused forest owner. This gap reflects that the profit-focused forest owner has to employ in most cases risker strategy to achieve its required terminal cash position level than the risk-focused forest owner. However, at a few points the gap is zero, e.g., when $\theta = 2.5$ million EUR. The explanation for the small gap is due to hedging opportunities being limited as all forest stands follow the same pine pulpwood price uncertainty. The gap would be wider if there were other assets, which could be used to hedge each other's risks.

Figure 2.9 is also useful for analysis of the terminal cash position profile. For example, the forest owner can be rather confident that the terminal cash position is greater than 1.5 million EUR for both strategies. It also shows that the probability of having more than 1.5 million EUR terminal cash position decreases initially steeply as the benchmark amount θ increases. Towards the higher values of θ the terminal cash position profile, however, gets flatter, in which the plateaus at the probability levels of 0.5, 0.2, and 0.03 are due to the binomial discretization.

The harvesting amounts as a function of time are represented for the profit-focused and risk-focused forest owners in Figure 2.10 when the benchmark terminal cash position $\theta =$ 1.69 million EUR. We choose the benchmark terminal cash position level $\theta = 1.69$ million EUR as it corresponds to roughly 93.8% chance of exceeding the benchmark of the risk-focused forest owner in Figure 2.9. This value is the closest to the 95% allowing thus better comparison between CCFAR and the satisficing risk measure.

The expected strategy of the risk-focused forest owner is to initially harvest roughly 60% of the forests that are the slowest growing and then the rest in the intermediate and terminal time states. This expected strategy resembles that of the risk-averse forest owner, Figure 2.6, who applies the CCFAR risk constraint. The reason is that the approaches are related because the risk-focused forest owner maximizes the probability of achieving a cash position greater than that of the worst 6.2% tail while the risk-averse forest owner minimizes the expected cash position in the worst 5% tail.

The expected investment strategy of the profit-focused forest owner is to harvest a few of the slow growing older forests immediately and let the faster younger forests grow until the

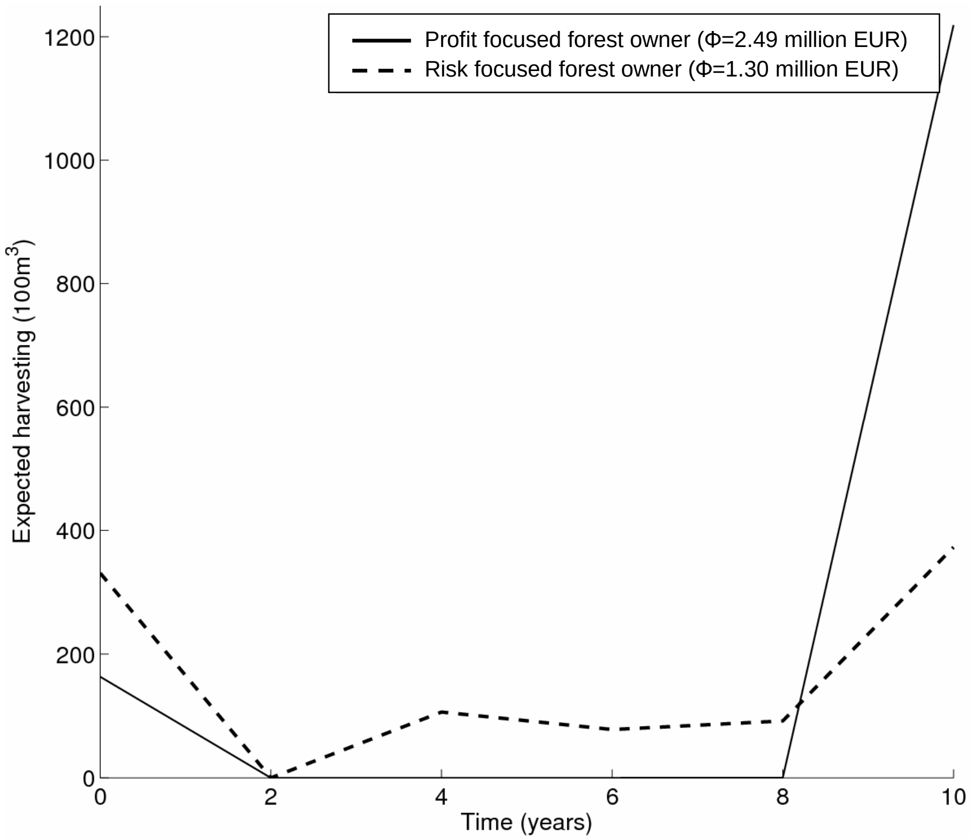


Figure 2.10 **Harvesting strategies using satisficing risk measure when $\theta = 1.69$ million EUR**

terminal time state with the aim of obtaining greater expected terminal cash position. The expected harvesting strategy of the profit-focused forest owner is almost identical with the risk-neutral forest owner, Figure 2.6, who applied CCFAR as the risk measure. The reason is that the approaches are comparable as (i) the risk-neutral forest owner maximizes the expected terminal cash position while keeping the strategy also efficient in terms of CCFAR and (ii) the profit-focused forest owner maximizes the probability of achieving a terminal cash position greater than that of the worst 6.2% tail while the expected terminal cash position is constrained to the maximum achievable level. Sensitivity analysis with respect to the volatility of the price (i.e., +/- 50% change in volatility) confirms that the expected harvesting strategies of the risk-averse and risk-focused forest owners are comparable as well as the expected harvesting strategies of the risk-neutral and profit-focused forest owners.

2.5. Extensions of Model

The computational experiments can be extended to overcome some of their limitations. First, the computational experiments focused on the pine pulpwood forest stands and omitted the other tree species and timber assortments. To some extent this limits the practical usability of the models as forest stands typically consist of a mix of different tree species, of which a certain portion can be processed for saw log and pulpwood (Heikkinen 2003). One possibility to include the different tree species and the purposes that they can be used for, is to model one price process, as was done in the experiments, but use it for capturing the basic timber price evolution and then add different offsets depending on the tree species and whether it can be processed for pulpwood or saw log purposes. Another possible approach is to model each of the prices of the timber products as separate uncertainties. This approach would, however, result in a computationally intensive model though it could be implementable using a low granularity discretization technique, such as Boyle et al. (1989).

The computational experiments can be extended to account for more practical details. One of these details is the change in the growth rate of forest stands as trees get older. In the computed experiments, this is not crucial as the planning horizon is only 10 years. However, if the planning horizon consists, for example of the whole growth cycle of the forest, from seeds till mature trees, then it would be essential to account for the reduction in the growth rate as the trees get older. This can be defined using the growth parameters g^{jt} and constraint (2.4). Including the change in the growth rate of the forest stands as time passes provides the forest owner an incentive to let the young quickly growing forest stands grow until they get old and grow slowly. Thus, risk-averse forest owners would be likely to wait longer before harvesting and risk-neutral forest owners likely to harvest earlier. Another detail that can be included in the computational experiment is thinning. Including thinning in the model increases the expected cash positions as it provides some income before the harvesting of the forest stand. Thinning revenues as well as fertilization and planting costs of the new forest stands after harvesting can be included in the model by specifying relevant cash-flow streams.

The proposed optimization model can be extended in several ways. First, it can be reformulated to include the real option of selling forest stands. This can be done by adding an additional decision variable for each time period for each forest stand. The selling price of a forest stand can be calculated, for example, as a perpetuity (e.g., Luenberger 1998) accounting for the possibility to plant and harvest the forest stand infinite times. Second, the proposed approach did not consider alternative investment opportunities, such as investments in financial securities. The optimization model could be re-formulated to include these alternative investment opportunities by specifying (i) decision variables for the purchase and the sale of the additional investment opportunities and (ii) scenarios for the stochastic processes of the values of the alternative investments. By including the alternative investment opportunities, it may be possible to reduce risks due to greater opportunities for diversification.

Additionally, the scenario generation method could be enhanced, among others by the following two ways. First, it could be extended to include mean reversion (e.g., Hahn and Dyer 2008), which may be present in the stochastic process of timber prices. By including mean reversion in the process the occurrence of extreme scenarios would be reduced and hence the extreme risks. Consequently, risk-averse forest owners would be likely to delay their harvesting and risk-neutral forest owners would be likely to harvest earlier, particularly if the price has got much higher than the mean where it is reverting to. Second, computational time of the models can be reduced if a smaller number of scenarios are generated using, for example the importance sampling method (e.g., Infanger 1993). This would facilitate the extension of the model to accommodate more time periods and uncertainties. Towards this end, the model did not account, for example an uncertainty in the forest growth. This can be modeled as an additional uncertainty if the forest stands are geographically close to each other, because their growth would be correlated due to similar weather conditions, for instance. By including the uncertainty in the forest growth, we expect that risk-averse forest owners would harvest their forests even earlier because waiting would imply greater risks.

Finally, while the extreme risk that is measured in this chapter focuses on the market risk in the worst 5% of the scenario outcomes, the extreme risk could be also understood as rarely occurring catastrophic events, such as forest fires. These are considered for example by Mills and Hoover (1982). To accommodate catastrophes, such as forest fires, this model could be re-formulated using, for example the extreme value theory (e.g., Embrechts et al. 1999). The extreme value theory based formulation would complement the business as usual approach and could be useful, among others in the evaluation of the price of an insurance against forest fires.

2.6. Implications for Harvesting of Forest Stands

While it is not possible to make general conclusions from the small data sample the numerical results suggest the following three implications when CCFAR and satisficing risk constraints are applied to the forest stand portfolio optimization. First, reducing CCFAR risk reduces the expected terminal wealth. The more the CCFAR risk is curtailed, the greater the reduction of the expected terminal wealth is, as the outcomes contributing to CCFAR risk become more likely to occur. Second, applying several CCFAR constraints concurrently can be used to model the forest owner's risk preferences at intermediate time periods and with different confidence levels. In particular, we show that if risk constraints are enforced only at the terminal period, this may not reduce the intermediate period risks the management of which may be of great importance if the forest owner is close to financial distress. Third, we demonstrate that the satisficing risk measure can be helpful in analyzing the expected cash position profile, i.e., what are the probabilities of achieving certain levels of expected cash positions under optimal decisions. Besides, satisficing risk measure may be more intuitive than CCFAR because it does not require the specification of a probability level but instead levels for the cash positions.

In the forest portfolio setting, the results of the experiments indicate that risk-neutral, perhaps industrial, forest owners harvest their forests later than more risk-averse, possible non-industrial, forest owners. This is because by allowing the forests grow further, the harvestable amount and expected terminal wealth increase with the risk of lower timber prices. This finding contradicts with the results of Hugonnier and Morellec (2007), which conclude that a risk-averse investor would invest later than a risk-neutral one. In their model, however, the investor does not own the risky asset and is waiting for the optimal time to acquire it, which is why it is better for him to delay the decision. By contrast, in this chapter, the risk-averse forest owner owns the (growing) stock of timber and is hesitant to be left with forests, when the price might decrease. Consequently, the behaviour of the risk-averse investor depends on the ownership of the asset.

The developed framework can be re-formulated for other natural resources management problems, for example in mining, or petroleum extraction industries, where extraction strategies are developed for portfolio of assets under commodity price uncertainty. The modeling approach is computationally tractable to multi-period problems of realistic size. This framework holds promise also in contexts where several uncertainties must be accounted for, as is the case, for example, when the forest stand consists of multiple species of trees or the amount of timber is uncertain. Thus, one avenue for future research is to analyze the value of information of obtaining more accurate estimates of the amount of harvestable timber using, for example a laser-scanning technology (Naesset 1997) under timber amount and price uncertainties.

Chapter 3
Optimization of Electricity Retailer's Contract Portfolio Subject to Risk Preferences

Chapter Summary

When an electricity retailer faces volume risk in meeting load and spot price risk in purchasing from the wholesale market, conventional risk management optimization methods can be quite inefficient. For the management of an electricity contract portfolio in this context, we develop a multistage stochastic optimization approach, which accounts for the uncertainties of both electricity prices and loads, and which permits the specification of conditional-value-at-risk requirements to optimize hedging across intermediate stages in the planning horizons. Our experimental results, based on real data from Nordpool, suggest that the modeling of price and load correlations is particularly important. The sensitivity analysis is extended to characterize the behavior of retailers with different risk attitudes. Thus, we observe that a risk-neutral retailer is more susceptible to price-related than load-related uncertainties in terms of the expected cost of satisfying the load, and that a risk-averse retailer is especially sensitive to the drivers of the forward risk premium.

3.1. Issues in Electricity Contract Portfolio Optimization

Electricity retailers face the problem of meeting instantaneous and variable loads that they may need to satisfy by purchasing electricity from wholesale power markets through spot and forward contracts. Optimizing this process is socially important and analytically challenging, incorporating volume as well as extreme price risks (e.g., Andrews 1995, Dahlgren et al. 2003). Wholesale power is increasingly being produced and traded via exchanges as an energy commodity, but its stochastic characteristics and risks are influenced by its delivery as an essential service to end-users. As a consequence, with companies facing uncertainties about their future loads as well as prices, the development of optimization models that allow power utilities to make appropriate production and trading decisions to maximize expected profits within specific risk constraints (e.g., Mo et al. 2001, Conejo et al. 2002, Ni et al. 2004, Fleten et al. 2002, Vehviläinen and Keppo 2003, Makkonen 2005, Liu and Wu 2006, Denton et al. 2003) presents extreme and special characteristics compared to other commodities and financial markets (e.g., Bunn 2004, Takriti et al. 2000). Electricity cannot be stored, but customers expect a high standard of service, and thus utilities bear load as well as price risk. Furthermore, spot price and load are correlated, often in a nonlinear manner, as in the example we report later where the correlation is stronger at higher levels of load. Both load and price time series exhibit daily, weekly and annual seasonality, volatility clustering (periods of low and high variance in the time series), mean reversion (tendency for the time series to revert to a stationary average), and in the case of prices, forward risk premiums (persistent differences between the forward prices and their expected spot prices) are amplified through the irregular, but not infrequent, spot price spikes that emerge at times of resource scarcity. A distinctive methodological challenge is, therefore, to formulate a multi-period contract portfolio that incorporates the correlated price and demand risks, which both evolve stochastically in a path-dependent processes, such that risks are managed efficiently throughout the contracting horizon.

Conventional approaches to constructing the forward contract portfolio have approximated the stochastic processes of the electricity prices and loads using simulations, moment matching, and models adapted from financial markets. These, however, have not included the correlation between price and load. For example, Doege et al. (2006) simulates uncertainties accounting for mean-reversion based on an extended Ornstein-Uhlenbeck process (Burger et al. 2004), Eichhorn et al. (2004b) construct their scenario trees using Monte-Carlo simulation and a scenario reduction technique (Heitsch and Römisch 2003), Fleten et al. (2002) uses scenarios that are based upon user-specified moments; whilst various financial market models have been used in electricity markets to model options and the dynamics of the forward prices (e.g., Clewlow and Strickland 1999, 2000, Koekebakker and Ollmar 2005, Manoliu and Tompaidis 2002, Benth et al. 2003). Overall, there exists an extensive line of research in scenario generation techniques (e.g., Gröwe-Kuska et al. 2003, Pennanen 2005, Dupacova et al. 2000, Høyland and Wallace 2001, Kouwenberg 2001, Pflug 2001), but, as far as we are aware, contract portfolio optimization within power risk management has not adequately reflected the correlation between load and spot prices. In this chapter, we seek to be innovative in adapting the HSS scenario tree building method (Ho et al. 1995, 1998, Peterson and Stapleton 2002) to capture this correlation within an optimized contract risk management process.

In risk management, research has mostly focused on extreme risks. For example, Vehviläinen and Keppo (2003) focus upon "value-at-risk" (VAR) measures, which are the extreme fractiles of the loss distributions, to constrain expected losses at a given level of confidence. But, although VAR is the de facto standard for risk compliance monitoring in the financial sector (e.g., RiskMetrics Group 2009), it is not a “coherent” (defined later) risk measure (Szegö 2002, Alexander and Baptista 2002, Embrechts et al. 1999, Uryasev 2000, Danielsson et al. 2001) and hence may not capture correctly the portfolio diversification benefits. Consequently, Conditional-VAR (CVAR), which measures the weighted average loss of the tail events, for a given fractile, is “coherent” and theoretically preferable (Uryasev 2000). Furthermore, since it can be formulated using linear programming (Rockafeller and Uryasev 2000), CVAR constraint portfolio optimizations have gained popularity (e.g., Doege et al. 2006, Eichhorn et al. 2004b,a, Cabero et al. 2005, Jabr 2005). Hence, we use CVAR as our key risk measure and show that by specifying multiple constraints in intermediate time periods as well as at the end, it is possible to control for risk throughout the contract spanning horizon.

Specifically, we develop a contract portfolio optimization method, using multistage stochastic optimization (e.g., Birge and Louveaux 1997), formulated primarily from the perspective of an electricity retailer who is contractually obliged to fulfill an uncertain demand (i) by buying electricity from the spot market and (ii) by hedging spot price exposure with forward contracts for later delivery of electricity. The retailer seeks to minimize the expected cost of establishing these contracts subject to various risk constraints (e.g., Doege et al. 2006, Eichhorn et al. 2004b,a). The problem is also analogous to that faced by an electricity generator who must produce electricity at an uncertain load level and sell this electricity at an uncertain spot price in a setting where it can also use forward contracts for hedging (e.g., Sen et al. 2006, Frauendorfer and Güssow 2002, Nasakkala and Keppo 2005). In this journal, this topic has been considered from the generator side by Conejo et al. (2008), Pineda et al. (2008) and in a retailer setting by Carrión et al. (2007), Gabriel et al. (2002, 2006), Fleten and Pettersen (2005), Baldick et al. (2006), Oum and Oren (2009). We extend these approaches by considering a dynamic forward portfolio. Hence, the retailer can purchase and sell forwards over multiple time periods depending on the evolution of the electricity prices and loads.

The contract portfolio optimization model presented here is innovative in that it integrates (i) correlation between spot price and demand, (ii) risk premiums in forward contracts, and (iii) temporal risk preferences in intermediate time periods over the contracting horizon. Results from numerical experiments with real data from Nordpool indicate that it is essential to model the demand and price correlations to achieve efficiency. They also yield some behavioral insights. For example, a risk-neutral retailer is more susceptible to price-related than load-related uncertainties in terms of the variability in the cost of satisfying the demand, whereas a risk-averse retailer is more sensitive to the risk premium and demand-related uncertainties.

The chapter is organized as follows. Section 3.2 introduces the decision problem, section 3.3 develops the portfolio optimization approach, and section 3.4 presents numerical results that are based on empirical data. Section 3.5 concludes with a discussion of practical implications and future research directions.

3.2. Decision Problem of Electricity Retailer

The problem is formulated from the perspective of the electricity retailer, who has to serve electricity demand through purchases from the spot and forward wholesale markets. However, both the demand and the spot electricity prices are uncertain. They are both assumed to follow a mean reverting processes, i.e., deviations from the local average price and load are expected to revert back to the local averages. This is a standard model in power and other energy commodities (Denton et al. 2003, Skantze et al. 2000, Benth and Karlsen 2005). Furthermore, deviations from the averages show volatility clustering, i.e., periods of high and low volatilities, again a standard heteroscedastic characteristic of power prices. In addition, we model the nonlinear relation between price and demand with the correlation coefficient increasing exponentially with respect to demand. The service costs of the retailer, without forward contracts, are the simple product of spot price and load. The risks of the retailer are the extreme service costs that occur when both load and spot prices are high. The retailer can reduce its exposure to risks by purchasing forward contracts for later delivery periods, e.g., in the Nordic Power Exchange Nordpool there are daily contracts available for up to nine days ahead, weekly contracts for up to six weeks ahead, monthly forwards for up to six months ahead, as well as quarterly and yearly contracts for several years ahead (see Figure 3.1). As with the other liquid forward markets, e.g., UK, Germany, the products traded become increasingly aggregated as the contract extends further into the future. Typically in Europe, traders will deal mainly in baseload contracts (i.e., continuous supply) from day ahead to three years ahead, Over the quarterly and weekly periods, the demand profile will be coarsely hedged with a simple mixture of two products, peakload (i.e., continuous power for the whole daytime, e.g., 8am to 8pm) and baseload. Only at the daily, or day-ahead, spot market or power exchange, would the expected demand be re-profiled from the two baseload and peakload products into hourly positions. This progression of granularity is necessary in order to concentrate the liquidity in trading, but despite this, many forward markets in Europe have liquidity problems. Particularly in markets with active, liquid forward trading, spot trading typically accounts for less than a few percent of the total volume, and is mainly associated with the re-profiling the peak and base contracts into hourly (or half-hourly in the UK) physical commitments. Risk management therefore evolves in several horizons: a longer term portfolio of quarterly and annual contract, a mid-term portfolio of weekly and monthly products, and short-term day-ahead to daily operations trading. In this chapter we are concerned with the mid-term horizon, which tends to be the most active.

The retailer can adjust the contract portfolio within the horizon in each consecutive time period by selling some of the existing contracts or by purchasing additional contracts. Forward contracts are likely to involve risk premiums, i.e., the forward price may differ from the expected spot price due to the different risk aversions between supply and demand participants in the market or their relative market power (Kristiansen 2004). In our analysis we treat "forward" and "futures" contracts as similar (and use the terms interchangeably), even though as products they differ in their implications on whether the contracts will ultimately lead to physical delivery or a purely financial settlement at expiry. Since, we

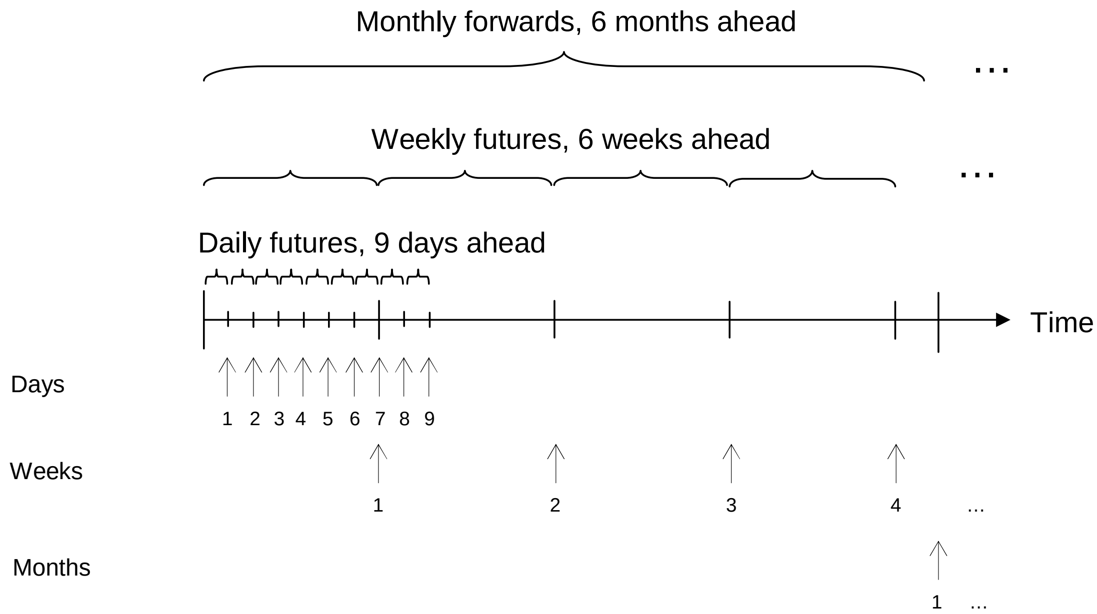


Figure 3.1 Daily and weekly future contracts and monthly forward contracts

are assuming a mid-term horizon in a market sufficiently liquid to allow participants to trade out of physical positions, these become effectively identical in our analysis.

The retailer's optimal contract portfolio is computed using modules for scenario generation and contract portfolio optimization. The scenario generation module takes (i) forward prices, (ii) expected loads, (iii) conditional standard deviations and mean reversions of spot price and load, (iv) forward premiums, and (v) correlation parameters as exogenous input. The forward prices are observed directly from the market whilst the other parameters can be estimated using historical time series data. Based on the estimated parameters, the discrete time scenario tree accounting for the unique characteristics of the stochastic processes of the spot price and demand are generated. The second module uses the generated scenario tree and optimizes the contract portfolio whilst accounting for the time dependent risk constraints. This provides optimal purchasing and selling decisions for contracts at the specific time points as well as the contingency plan. Overall, it is assumed that the retailer's objective is to minimize the expected cost of the contract portfolio whilst meeting its risk constraints.

Note that the existence of long-term bilateral electricity supply contracts, which the retailer can use to secure a pre-specified amount of electricity at a pre-specified price, or own-generation, do not affect this model. The reason is that their inclusion does not remove the risk management need because a retailer still needs to adjust the remaining portion of the electricity load via spot market and use contracts to hedge these risks (Gabriel et al. 2006). Also, because the problem is formulated from the cost minimization perspective, there is no need to model the retailer's revenues that are received from the end-users.

3.3. Electricity Contract Portfolio Model for Retailer

3.3.1. Scenario Tree Generation

We define the following parameters

$P_t,\ L_t$ instantaneous electricity spot price and load, i.e., price and load per time unit when the time interval is infinitesimally small,
$c_P,\ c_L$ mean reversion factors of price and load,
$\theta_t,\ \vartheta_t$ instantaneous means to which price and load revert,
$\sigma_{\widetilde{P}_t},\ \sigma_{\widetilde{L}_t}$ instantaneous standard deviations of price and load, and,
$\rho_t\ \in$ [-1,1] instantaneous correlation between price and load.

The scenario tree is generated for a finite planning horizon over $t = 0,...,T$ time periods. The uncertainties pertain to the instantaneous electricity spot price P_t and load L_t, which follow mean-reverting Ornstein-Uhlenbeck stochastic process

$$\begin{aligned} d\widetilde{P}_t &= c_P(\theta_t - \widetilde{P}_t)dt + \sigma_{\widetilde{P}_t} dW_{1,t} \\ d\widetilde{L}_t &= c_L(\vartheta_t - \widetilde{L}_t)dt + \sigma_{\widetilde{L}_t} dW_{2,t}, \end{aligned} \tag{3.1}$$

where $\widetilde{P}_t = ln(P_t/E(P_t))$, $\widetilde{L}_t = ln(L_t/E(L_t))$, $dW_{1,t}$, and $dW_{2,t}$ are correlated Wiener processes such that $E[dW_{1,t}, dW_{2,t}] = \rho_t dt$. These processes are modeled with the extension of the HSS scenario tree (Peterson and Stapleton 2002) that generates a recombining discrete time scenario tree of two correlated binomial trees. While the generated scenarios recombine forming a lattice, see Figure 3.2, we refer to it as a tree because the optimization problem is path dependent and thus needs to be formulated over a scenario tree. Binomial trees are used because the computational burden is thus lower than if trees had greater number of branches. The number of scenarios grows exponentially with respect to the number of time periods and child nodes, i.e., by using 2 binomial trees the number of scenarios in period t is 2^{2t}. Binomial trees are commonly used in finance to represent the path-dependent evolution of an uncertainty (Cox et al. 1979, Black and Scholes 1973).

The advantages of the extension of the HSS scenario generation method are, among others, that it (i) matches initially the market observed future prices and (ii) provides an arbitrage free pricing environment. The method can be used to approximate a correlated multivariate-lognormal process exhibiting mean-reversion and volatility clustering. Thus, it can capture essential characteristics of the electricity price and load processes if applied at the daily, weekly, or monthly intervals in which the future and forward contracts are also specified at the Nordpool. The HSS method does not, for instance incorporate spikes, which are more pronounced in higher frequency, hourly level (Longstaff and Wang 2004).

The steps of building the HSS scenario tree for correlated price and load consist of the computation of (i) nodal values for price and load, (ii) scenario probabilities, and (iii) future prices.

Nodal values

To compute nodal values, we define movements in the scenario tree as follows. Let s^0 be the base scenario in period $t=0$ and S^t be the set of all scenarios in period t; there are 2^{2t} such scenarios because we have two uncertainties that are modeled as binomial trees. A scenario $\mathbf{s^t}$ is represented as a $2\times t$-matrix whose elements consist of binary variables $s^t_{L,j}$ for load movements and $s^t_{P,j}$ for price movements in period j, $j=1,...,t$

$$S^t = \{\mathbf{s^t} \in \mathbb{R}_{2\times t} | s^t_{i,j} \in \{0,1\}, \quad i=L,P, \quad j=1,...,t\}.$$

The unique immediate predecessor of scenario $\mathbf{s^t} \in S^t$ $(t>0)$ is $b(\mathbf{s^t}) = \mathbf{s^{t-1}} \in S^{t-1}$ such that $s^{t-1}_{i,j} = s^t_{i,j}$, $i=L,P$, and $j=1,...,t-1$. All the preceding scenarios of $\mathbf{s^t}$ are denoted by $B(\mathbf{s^t})$ (see Figure 3.2).

The scenario matrices are interpreted so that $s^t_{L,j}=1$ means that the load in period j is higher compared to the expected load as seen on $b(\mathbf{s^{t-1}})$, while $s^t_{L,j}=0$ corresponds to a lower load in period j compared to the expected load as seen on $b(\mathbf{s^{t-1}})$. Likewise, higher and lower prices compared to the expected price as seen on $b(\mathbf{s^{t-1}})$ are denoted by $s^t_{P,j}=1$ and $s^t_{P,j}=0$.

We also define

$P(\mathbf{s^t})$ electricity spot price (EUR/MWh) in period t in scenario $\mathbf{s^t} \in S^t$,

$L(\mathbf{s^t})$ electricity load (MWh) in period t in scenario $\mathbf{s^t} \in S^t$,

u_{P_t}, d_{P_t} multiplicative increase and decrease in electricity spot price in period t when $s^t_{P,j}=1$ and $s^t_{P,j}=0$ respectively,

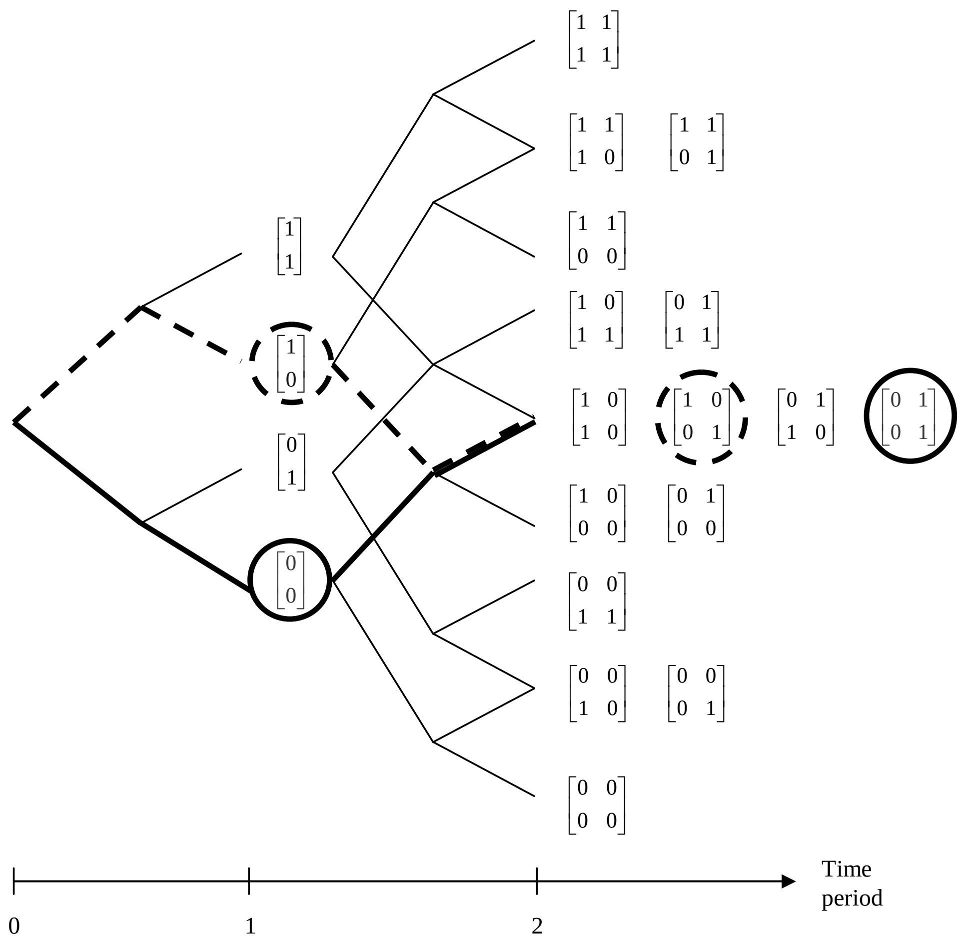


Figure 3.2 **Scenario tree with two example scenarios highlighted**

u_{L_t}, d_{L_t} multiplicative increase and decrease in electricity load in period t when $s^t_{L,j} = 1$ and $s^t_{L,j} = 0$ respectively,

$n_P(\mathbf{s^t})$ number of multiplicative increases in the price during periods $k = 0, ..., t$ in scenario $\mathbf{s^t} \in S^t$, i.e., $n_P(\mathbf{s^t}) = \sum_{j=1}^{t} s^t_{P,j}$,

$n_L(\mathbf{s^t})$ number of multiplicative increases in the load during periods $k = 0, ..., t$ in scenario $\mathbf{s^t} \in S^t$, i.e., $n_L(\mathbf{s^t}) = \sum_{j=1}^{t} s^t_{L,j}$,

$E_0(P_t)$, $E_0(L_t)$ expected spot price (EUR/MWh) and expected electricity load (MWh) in period t as seen at time 0,

σ_{P_t}, σ_{L_t} conditional standard deviations of electricity spot price and load in period t,

$M_0(t)$ market observed futures prices as seen at time 0 for delivery period t, and,

π_t risk premium (in % of future prices) for t periods later starting future, which can be estimated, for example based on historical future and realized spot prices.

The electricity spot price $P(\mathbf{s^t})$ and electricity load $L(\mathbf{s^t})$ in scenario $\mathbf{s^t}$ are as follows (Ho et al. 1995)

$$P(\mathbf{s^t}) = u_{P_t}^{n_P(\mathbf{s^t})} d_{P_t}^{t-n_P(\mathbf{s^t})} E_0(P_t), \tag{3.2}$$

$$L(\mathbf{s^t}) = u_{L_t}^{n_L(\mathbf{s^t})} d_{L_t}^{t-n_L(\mathbf{s^t})} E_0(L_t), \tag{3.3}$$

where

$$\begin{cases} u_{P_t} = (2e^{2\sigma_{P_t}})/(1+e^{2\sigma_{P_t}}) \\ d_{P_t} = 2/(1+e^{2\sigma_{P_t}}) \end{cases}, \tag{3.4}$$

$$\begin{cases} u_{L_t} = (2e^{2\sigma_{L_t}})/(1+e^{2\sigma_{L_t}}) \\ d_{L_t} = 2/(1+e^{2\sigma_{L_t}}) \end{cases}. \tag{3.5}$$

The expected spot prices $E_0(P_t)$ can be obtained from the observed futures prices by removing the risk premiums (Shawky et al. 2003); hence, the model can be matched to observed prices of futures contracts

$$E_0(P_t) = \frac{M_0(t)}{1+\pi_t} \quad \forall t = 0, ..., T. \tag{3.6}$$

Scenario probabilities

We define

$p(\mathbf{s^t})$ scenario $\mathbf{s^t} \in S^t$ probability in period t,

$p_P(\mathbf{s^t})$, $p_L(\mathbf{s^t})$ probabilities of the higher price and load in period t in scenario $\mathbf{s^t} \in S^t$ compared to the expected levels as seen on $b(\mathbf{s^t})$,

$\rho(\mathbf{s^t})$ correlation of electricity price and load in period t in scenario $\mathbf{s^t} \in S^t$,

N, λ correlation parameters, and

$F(\mathbf{s^t}, t')$ future contract prices as seen in period t in scenario $\mathbf{s^t} \in S^t$ for the contract period t', $t' > t$.

Scenario probabilities $\forall \mathbf{s^t} \in S^t$, $t = 1, ..., T$ can be computed by using the probabilities of the higher price $p_P(\mathbf{s^t})$ and load $p_L(\mathbf{s^t})$ compared to the expected levels as seen on $b(\mathbf{s^{t-1}})$,

$$\begin{aligned} p(\mathbf{s^t}) = {} & \textstyle\prod_{j=1}^{t} p_P(b^{t-j}(\mathbf{s^t}))^{s^t_{P,j}} \times [1 - p_P(b^{t-j}(\mathbf{s^t}))]^{1-s^t_{P,j}} \\ & p_L(b^{t-j}(\mathbf{s^t}))^{s^t_{L,j}} \times [1 - p_L(b^{t-j}(\mathbf{s^t}))]^{1-s^t_{L,j}}. \end{aligned} \tag{3.7}$$

Probabilities of the higher price $p_P(\mathbf{s^t})$ and load $p_L(\mathbf{s^t})$ compared to the expected levels as seen on $b(\mathbf{s^{t-1}})$, can be computed following Peterson and Stapleton (2002), $t = 1, ..., T$

$$\begin{cases} p_P(\mathbf{s^t}) = \frac{1}{\ln(u_{P_t}/d_{P_t})}\Big[\alpha_P(\mathbf{s^t}) + \beta_P \ln\frac{P(b(\mathbf{s^t}))}{E_0(P_{t-1})} + \gamma_P(\mathbf{s^t})\ln\frac{L(b(\mathbf{s^t}))}{E_0(L_{t-1})} + \\ \quad \delta_P(\mathbf{s^t})\ln\frac{L(\mathbf{s^t})}{E_0(L_t)} - (-1+n_P(\mathbf{s^t}))\ln u_{P_t} - (1+t-n_P(\mathbf{s^t}))\ln d_{P_t}\Big] \\ \alpha_P(\mathbf{s^t}) = \frac{1}{2}\left[\beta_P(t-1)\sigma^2_{P_{t-1}} - t\sigma^2_{P_t} + \gamma_P(\mathbf{s^t})(t-1)\sigma^2_{L_{t-1}} + \delta_P(\mathbf{s^t})t\sigma^2_{L_t}\right] \\ \beta_P = 1 - c_P \\ \gamma_P(\mathbf{s^t}) = \rho(\mathbf{s^t})\frac{\sigma_{P_t}}{\sigma_{L_t}}(-1+c_L) \\ \delta_P(\mathbf{s^t}) = \rho(\mathbf{s^t})\frac{\sigma_{P_t}}{\sigma_{L_t}} \end{cases} \tag{3.8}$$

$$\begin{cases} p_L(\mathbf{s^t}) = \frac{1}{\ln(u_{L_t}/d_{L_t})}\Big[\alpha_{L_t} + \beta_L \ln\frac{L(b(\mathbf{s^t}))}{E_0(L_{t-1})} - (-1+n_L(\mathbf{s^t}))\ln u_{L_t} - \\ \quad (1+t-n_L(\mathbf{s^t}))\ln d_{L_t}\Big] \\ \alpha_{L_t} = \frac{1}{2}\left[\beta_{L_t}(t-1)\sigma^2_{L_{t-1}} - t\sigma^2_{L_t}\right] \\ \beta_L = 1 - c_L. \end{cases} \tag{3.9}$$

The probabilities of lower prices and loads compared to the expected levels as seen on $b(\mathbf{s^{t-1}})$ are one minus the probabilities of higher prices and loads compared to the expected levels as seen on $b(\mathbf{s^{t-1}})$. The increased correlation between load and price as a function of increasing load (i.e., similar to the increase in the demand elasticity of price) is modeled through an exponential function, which is supported by Nordpool's load and spot price data. The parameters N (scaling the correlation) and λ (representing the strength of the exponential relationship) for the following formulation can be estimated from the market or by using marginal cost supply function

$$\rho(\mathbf{s^t}) = Ne^{\lambda L(\mathbf{s^t})}. \tag{3.10}$$

Based on the estimated parameters N and λ, it is possible to confirm that the correlation remains between $[-1,\ 1]$ in all load levels, which are computed using equation (3.3). If this is not the case, then the violating correlations can be gapped to $[-1,\ 1]$, for example. In other words, $\forall \mathbf{s^t} \in S^t$, $t = 1, ..., T$ if $\rho(\mathbf{s^t}) > 1$ then set $\rho(\mathbf{s^t}) = 1$ and if $\rho(\mathbf{s^t}) < -1$ then set $\rho(\mathbf{s^t}) = -1$. If the violations occur frequently, it is worth investigating alternative specification for the correlation equation.

Future prices

Future prices are computed at each node in period t for the later delivery $t' > t$. We assume that the contract period lasts the whole period t', and hence the future price is equivalent to the conditional expected spot price multiplied by the risk premium for that period. Therefore the future price is

$$F(\mathbf{s^t}, t') = \frac{1}{p(\mathbf{s^t})} \left[\sum_{\mathbf{s^{t'}} \in S^t | \mathbf{s^t} \in B(\mathbf{s^{t'}})} p(\mathbf{s^{t'}}) P(\mathbf{s^{t'}}) \right] (1 + \pi_{t'-t}). \tag{3.11}$$

Scenario tree generation steps

The scenario tree can be generated through the following steps:

1. Obtain historical time series data regarding spot prices, future prices, and loads.

2. Estimate conditional standard deviations σ_{P_t} and σ_{L_t} using GARCH(1,1) model, for example.

3. Compute u_{P_t}, d_{P_t}, u_{L_t}, and d_{L_t} using equations (3.4-3.5).

4. Calculate expected spot prices $E_0(P_t)$ using equation (3.6), market observed futures $M_0(t)$, and estimated premiums π_t.

5. Estimate expected electricity loads $E_0(L_t)$ based on historical data or experts' opinions, for example.

6. Calculate electricity spot prices $P(\mathbf{s^t})$ and electricity loads $L(\mathbf{s^t})$ with equations (3.2-3.3).

7. Estimate N and λ based on historical time series data applying the least squares method to the linearized version of equation (3.10).

8. Calculate probabilities of the higher price and load in scenario $\mathbf{s^t} \in S^t$ compared to the expected levels as seen on $b(\mathbf{s^t})$ using equations (3.8-3.9) and finally the scenario probabilities $p(\mathbf{s^t})$ with equation (3.7).

3.3.2. Contract Portfolio Optimization

We define

$C(\mathbf{s^t})$ cash position in period t in scenario $\mathbf{s^t} \in S^t$,

a initial cash position,

r_t short rate at which cash accrues interest between periods $[t, t+1]$, $t = 0, ..., T-1$,

$x(\mathbf{s^t}, t')^+$, $x(\mathbf{s^t}, t')^- \in \mathbb{R}^+$ amount (MWh) of purchased and sold t' period electricity at time t in scenario $\mathbf{s^t} \in S^t$; if $t = t'$ contract is spot, if $t' > t$ future,

$x(\mathbf{s^t}, t')$ net amount (MWh) of electricity contracts at time t in scenario $\mathbf{s^t} \in S^t$, i.e., $x(\mathbf{s^t}, t') = x(\mathbf{s^t}, t')^+ - x(\mathbf{s^t}, t')^-$,

X^t set of all purchased future contracts, which delivery period ends in period t,

$\mathbf{M} \in \mathbb{R}_{T\times m}$ risk constraint matrix, $m \in \mathbb{Z}^+$,

R_{1,β_1}, ..., $R_{T,\beta_m} \in \mathbb{R}$ pre-specified risk tolerance levels measured in conditional-cash-flow-at-risk,

$\alpha_{i,j} \in \mathbb{R}$ auxiliary variables, $i = 1, ..., T$, $j = 1, .., m$,

$\beta_j \in [0, 1)$ the probability of a non-tail event, $j = 1, .., m$,

$\kappa_j(\mathbf{s^t}) \in \mathbb{R}$ auxiliary variables in period t in scenario $\mathbf{s^t} \in S^t$, $j = 1, .., m$, and

$RT_i \in \mathbb{R}$ reference target amount, which divides the scenarios into profit and loss scenarios, i=1,...,T.

The optimization problem is formulated using stochastic programming (e.g., Birge and Louveaux 1997) subject to cash-flow constraints, trading constraints, and risk management constraints. The stochastic programming approach is advantageous in our setting because it permits the introduction of risk constraints also in intermediate time periods. This would be practically impossible with dynamic programming approaches (e.g., Bertsekas 1995) where the intermediate nodes represent the maximum cash position when discounting from the terminal time period and hence do not account for the cash-flow impacts of past decisions (Krokhmal and Uryasev 2007).

Cash-flow constraints

In period $t = 0$, the cash position in base scenario s^0 is

$$C(s^0) = a - L(s^0)P(s^0) \tag{3.12}$$

where a is the initial cash position and $L(s^0)P(s^0)$ is the cost of acquiring electricity for satisfying the load in the base scenario.

In period $t = 1$, the cash position in scenario $\mathbf{s^1} \in S^1$ consist of three parts (i) cash position from the base scenario and interest on it, $C(s^0)(1 + r_0)$ (Gustafsson and Salo 2005) (ii) cost of spot contracts purchased in $\mathbf{s^1}$, $-L(\mathbf{s^1})P(\mathbf{s^1})$, and (iii) changes in the values of the future contracts purchased in the base scenario $\sum_{t'=1}^{T} x(s^0, t') \left[F(\mathbf{s^1}, t') - F(s^0, t')\right]$, i.e., futures contracts are marked-to-market in every period. These components can be generalized to periods $t=1,\ldots,T$ as follows[2]

$$\begin{aligned} C(\mathbf{s^t}) = & \underbrace{C(b(\mathbf{s^t}))(1+r_{t-1})}_{\text{previous cash position with interest}} - \underbrace{L(\mathbf{s^t})P(\mathbf{s^t})}_{\text{cost of spot}} + \\ & \underbrace{\sum_{i=0}^{t-1}\sum_{t'=t}^{T} x(\mathbf{s^i},t')\left[F(\mathbf{s^t},t') - F(b(\mathbf{s^t}),t')\right]}_{\text{futures marked-to-market}}. \end{aligned} \tag{3.13}$$

Trading constraints

We assume that the electricity retailer trades futures primarily for hedging purposes and not for speculating. Hence, we do not permit the short selling of futures contracts, (i.e., borrowing future contracts from a broker and selling it with the obligation to buy it back to the broker later), but permit the selling of previously purchased futures. These assumptions correspond to the following trading constraints, $t=1,...,T-1$

$$\begin{aligned} & x(s^0,t')^- = 0 && t' = 0,...,T \\ & x(\mathbf{s^t},t')^- \le \textstyle\sum_{\mathbf{s'}\in B(\mathbf{s^t})} x(\mathbf{s'},t') && t' = t+1,...,T. \end{aligned} \tag{3.14}$$

Risk management constraints

Extreme risks can be taken into consideration by using VAR or CVAR risk measures (e.g., Artzner et al. 1999, Rockafeller and Uryasev 2000). But although VAR is the de facto standard in the financial industry (e.g., RiskMetrics Group 2009), it is problematic in that it does not fulfil the subadditivity condition (Szegö 2002, Alexander and Baptista 2002, Embrechts et al. 1999, Uryasev 2000, Danielsson et al. 2001) of the following four requirements on coherent risk measure, stated for risk measure $\rho \in \mathbb{R}$ where x and y are random returns (Delbaen 2000).

1. Translation invariance $\rho(x+a) = \rho(x) - a \quad \forall\ a \in \mathbb{R}$.
2. Subadditivity $\rho(x+y) \le \rho(x) + \rho(y) \quad \forall\ x,y$.
3. Positive homogeneity $\rho(\lambda x) = \lambda\rho(x) \quad \forall\ \lambda \ge 0$.
4. Positivity $\rho(x) \le 0 \quad \forall x \ge 0$.

We apply CVAR that is a coherent risk measure and can be solved using linear (convex) optimization formulation of the (Rockafeller and Uryasev 2000). This formulation can be used for a cash-flow version, conditional-cash-flow-at-risk (CCFAR), with minor modifications as presented. Extreme risks can be curtailed throughout the planning horizon

[2] As we have a cost minimization problem the retailer's revenues that are received from the end-users are not included. If the model were formulated for maximizing profits, an analogous approach could be used where revenues, that are typically based on a pre-agreed price per consumed MWh, could be included by replacing $P(\mathbf{s^t})$ with $P(\mathbf{s^t})$ from which is subtracted the pre-agreed constant price.

by introducing concurrent CCFAR risk constraints at several confidence levels as follows, $\mathbf{s^t} \in S^t,\ t=0,...,T,\ i=1,...,T,\ j=1,..,m$

$$
\begin{aligned}
\mathbf{M} \quad &= \begin{pmatrix} R_{1,1} & . & R_{1,m} \\ . & . & . \\ R_{T,1} & . & R_{T,m} \end{pmatrix} \\
R_{i,j} \quad &\geq \alpha_{i,j} + \tfrac{1}{1-\beta_j} \sum_{\mathbf{s^i} \in S^i} \kappa_j(\mathbf{s^i}) \\
\kappa_j(\mathbf{s^i}) &\geq p(\mathbf{s^i})\,[RT_i - C(\mathbf{s^i}) - \alpha_{i,j}] \\
\kappa_j(\mathbf{s^i}) &\geq 0.
\end{aligned} \tag{3.15}
$$

We included in the above formulation reference target amounts RT_i. They allow to specify different reference, or benchmark, cash positions for each time periods shifting the CCFAR levels accordingly to reflect that the total cumulative benchmark costs increase in time.

Objective function and complete maximization problem

As in stochastic programming (Birge and Louveaux 1997), we maximize the expected cash position (i.e., minimize expected costs) in the terminal time period

$$
\max_{X^T,\ \alpha_{i,j},\ \kappa(\mathbf{s^t})} \sum_{\mathbf{s^T} \in S^T} p(\mathbf{s^T})C(\mathbf{s^T}), \tag{3.16}
$$

subject to constraints (3.12-3.15).

3.4. Numerical Results From Empirical Data

The experiments illustrate the key characteristics of stochastic optimization and its sensitivities to input parameters and concurrent risk constraints. The experiments were analyzed from the point of view of two different retailers of the electricity market: (i) a risk-neutral retailer who uses few forward contracts and seeks to minimize the expected cost of its portfolio and (ii) a risk-averse retailer who uses substantial forward contracting and seeks to minimize its extreme risks measured in CCFAR. The experiments also test the following hypothesis:

- H1: Increase (decrease) in premiums increases (decreases) the cost of hedged portfolio.

An increase in the premiums results in higher future prices that in turn increases the expected cost of the hedged portfolio, the more the futures are used.

- H2: Increase (decrease) in correlation increases (decreases) risk. High correlation means that load and spot are more likely to move together, which means that there are more extreme events and risk.
- H3: Increase (decrease) in mean reversion decreases (increases) risk. Stronger mean reversion is expected to keep the values closer to their mean resulting in less extreme scenarios and less risk.
- H4: Increase (decrease) in the conditional standard deviation of spot price or load increases (decreases) risk.

The optimization problems were solved with the Dash Optimization software Xpress®, run on a PC with 700 MHz Pentium III processor, 256 MB of RAM, and Windows XP operating system. The running time of the optimization models was about five seconds.

3.4.1. Data

We consider the mid-term horizon problem, with weekly and monthly level contracts, as these are the most actively traded (Rasool et al. 2009), and may therefore represent a crucial stage in contract portfolio risk management process. This is without loss of generality, however, since the analogous approach can be used over different contract portfolio optimization horizons. We consider a six-week time horizon, which includes all forward contracts in the market with one-week periods. This resulted in a tractable model, which did not call for the use of scenario reduction methods (e.g., Heitsch and Römisch 2003, Gröwe-Kuska et al. 2003). At the same time, this horizon was long enough for testing the above hypotheses and for exploring the properties of the model and its sensitivities to input parameters. The weekly level of aggregation allowed us to ignore spot market spikes and issues of daily seasonality.

Weekly market data on six weeks futures were obtained on 24.3.2006 from the Nordic power exchange Nordpool. The premiums of the futures were estimated for this six-week period based on Nordpool's future and spot prices from the past seven years (weeks 13-18 in 1999-2005). The estimation of future premiums with a least squares approach resulted in the linear equation $\Pi_t = 0.0183t + 0.1428$ ($R^2 \approx 0.8$) that estimates the premiums for six one-week long futures $t = 1, 2, 3, 4, 5, 6$ each of which started from where the previous future ended as seen on 24^{th} of March, for a similar method of estimating premiums see e.g., Shawky et al. (2003). Our estimated coefficient of t is twice the magnitude of Shawky et al. (2003). It is also positive as in their study suggesting that, within the estimation period, the premium increases the further ahead the starting date of the future contract is. This can be due to an increase in the risk aversion of power generators although the size of our data set does not warrant general conclusions. In an extensive study focusing on forward contracts, Cartea and Villaplana (2008) show that the premium is seasonal and can be even negative when the standard deviation of the electricity load is low.

We considered the future $t = 1$ as the weekly spot price after accounting for the risk premium. The conditional weekly standard deviations for spot prices were estimated from the same seven-year data set. This was done by (i) taking a 26-week moving average of the data and (ii) modeling the standard deviation of the difference of the moving average and the actual data with GARCH(1,1) $\sigma^2_{P_t} = \omega_P + \phi_P \varepsilon^2_{t-1} + \theta_P \sigma^2_{P_{t-1}}$ so that the long term trend and seasonal effects were filtered out. The estimated parameters were $\omega_P = 56.02$, $\phi_P = 0.85$, and $\theta_P = 0.35$.

For the electricity load, we obtained the weekly loads in Finland for the period 1990-2005 from Energiateollisuus (2006), of which we used 1% (comparable to the load in an average small town). The expected weekly electricity loads were estimated by taking an average load change in the past (weeks 13-18 in 1990-2005) and applying these expected changes to forecast expected loads in weeks 13-18 in 2006. The conditional weekly standard deviations for the loads were estimated from the same data set applying a GARCH(1,1) model $\sigma^2_{L_t} = \omega_L + \phi_L \varepsilon^2_{t-1} + \theta_L \sigma^2_{L_{t-1}}$ for filtered data (similar to the estimation of the conditional spot price standard deviations). The estimated parameters were $\omega_L = 1.17$, $\phi_L = 0.44$, and $\theta_L = -0.18$.

The estimation of load and spot price correlation parameters was based on weekly data for the 6 months prior to 24.3.2006, which reflected the capacity of electricity generation at the time the model was run (unlike the full set of data from seven years). The estimation was conducted by dividing the data into four segments based on load and evaluating the correlations in the segments, whereafter the least squares method was applied to the linearized version of equation (3.10). This resulted in $N = 0.08$ and $\lambda = 0.1$. The mean reversion parameters were obtained by fitting with least squares method linear equations for the mean reversion processes of the spot price and load during weeks 13-18 in years 1999-2005. The means to which the spot and the load values revert are the expected spots and the expected loads for the corresponding week as seen in the beginning of the week 13. The estimated mean reversion parameters for the spot and the load were 0.2 and 0.4 respectively. The data of the experiments is summarized in Table 3.1.

Table 3.1 Data of Experiments (weekly future prices as seen on 24.3.2006 in EUR/MW contract and expected loads in GWh)

Delivery period	Future price	Conditional standard deviation of spot	Premium on spot	Expected load	Conditional standard deviation of load
27.3-2.4	54.69	0	0.161	18.94	0
3.4-9.4	54.40	0.162	0.179	18.67	0.058
10.4-16.4	52.50	0.199	0.199	17.94	0.055
17.4-23.4	52.40	0.211	0.216	17.77	0.056
24.4-30.4	51.95	0.219	0.234	16.99	0.059
1.5-7.5	50.00	0.232	0.253	16.16	0.062

Mean reversion for spot price $c_P = 0.2$ and load $c_L = 0.4$, correlation parameters $N = 0.08$ and $\lambda = 0.1$ (which implied that the effective range of the correlation coefficient was between 30% and 70%), the yearly interest rate was 2%, and trade fee was 0.03 EUR/MWh.

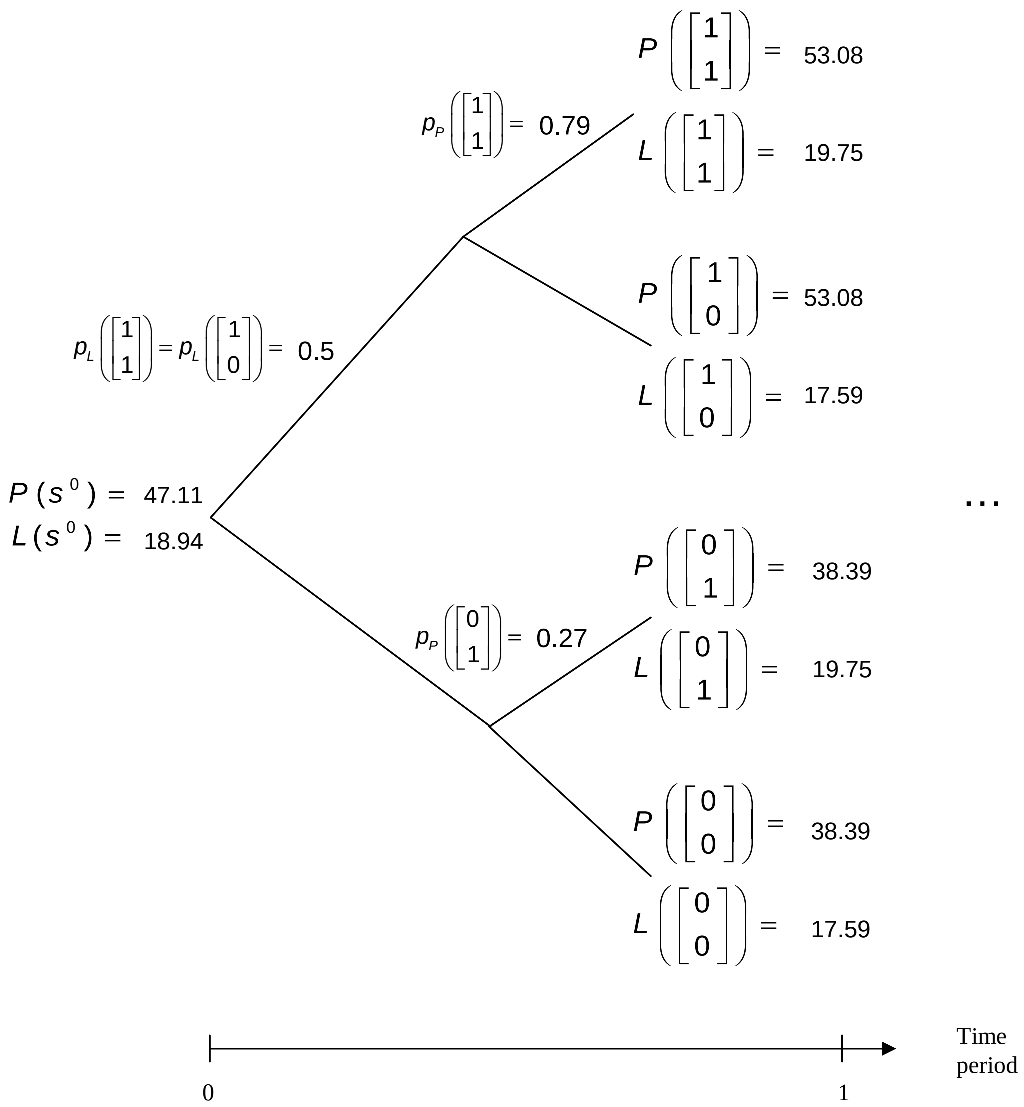


Figure 3.3 Generated scenarios for periods $t = 0$ and $t = 1$

Some simplifications and adjustments were made in the experiments. In the scenario tree generation, probabilities of the higher an lower prices and loads compared to the expected levels were rounded to obtain values between zero and one, as suggested by Ho et al. (1995); this is because the HSS model can, at times, result in probabilities that are either negative or greater than one if correlation between the modeled variables is very strong (Ho et al. 1995).[3] This rounding of probabilities between zero and one can mean that the tree does not match the values of the observed futures perfectly. To avoid this, the nodal values were re-scaled after the tree was created and a perfect match achieved, for similar approach see Peterson and Stapleton (2002). Peterson and Stapleton (2002) also demonstrate that re-scaling can be done as "the computation of the probabilities is independent of the means of the process" and thus the structure of the stochastic process remains correct. Figure 3.3 shows the scenarios in time periods $t=0$ and $t=1$, after re-scaling. In the terminal period, $t=5$, there are $4^5=1024$ scenarios and the ranges of values that load and price can obtain, given $p(\mathbf{s^t})>0$, are $[13.39, 19.42]$ and $[11.57, 117.75]$ respectively.

Taxation issues were ignored and it was assumed that the purchased contracts do not influence contract prices. We also assumed that future contracts can be purchased in any size of units, although in reality the minimum contract volume is 1 MW.

3.4.2. Results

The experiments were conducted to compare the mean-CCFAR efficiency of (i) our proposed stochastic optimization, (ii) periodic optimization, and (iii) a fixed allocation strategy (in which futures were purchased according to the following fixed percentages of the load 80%, 70%, 60%, 50%, and 40% for the 1, 2, 3, 4, and 5 weeks dated futures respectively). Periodic optimization is conducted over the same scenario tree using equations (3.12-3.16) but replacing $x(\mathbf{s^t},t')^+$, $x(\mathbf{s^t},t')^-$, and $x(\mathbf{s^t},t')$ with period specific decisions $x(t,t')^+$, $x(t,t')^-$, and $x(t,t')$ respectively. In other words, the periodic optimization approach determines the optimal contract portfolio at $t=0$ and how it is adjusted in consecutive time periods regardless of the scenario specific realization. Thus, period optimization ignores path dependency and possibilities to adjust the portfolio based on the scenario realizations.

Figure 3.4 shows the mean-efficient frontiers with respect to the 6 week 95% CCFAR, in which losses relate to an initial budget of 5.2 million EUR. The stochastic optimization is the most efficient one with respect to the expected cost and CCFAR. For example, a

[3] We observed that this phenomenon occurred also if the mean reversion parameters or conditional standard deviations were high.

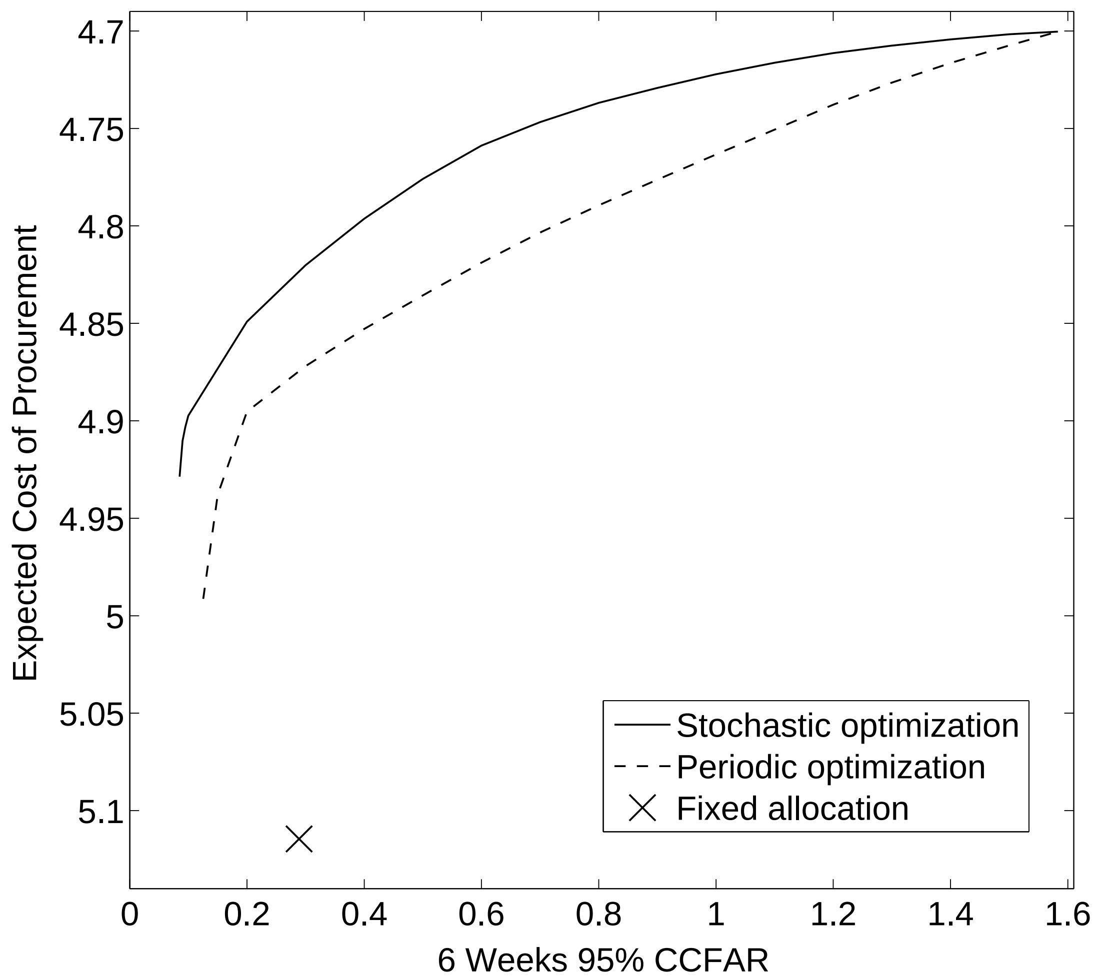


Figure 3.4 **Comparison of stochastic optimization, periodic optimization, and fixed allocation (figures in million EUR)**

comparison of stochastic optimization with fixed allocation indicates that the same risk level (as measured by 95% CCFAR) can be attained at about 5.6% lower cost in relation to the initial budget. The gap between the methods can be expected to increase if the risks increase due to changes in correlation, standard deviations, or mean reversions.

From the point of view of the risk-averse retailer, which corresponds to the leftmost end of the curve, the stochastic optimization approach provides significant benefits in reduction of expected cost as contract portfolio is efficiently managed. For the risk-neutral retailer, which corresponds to the rightmost end of the curve, the benefits of the stochastic optimization method are less significant because only a few futures are purchased.

When the hypotheses H1-H4 were tested with respect to changes in the input parameters, these hypothesis were validated (see Figure 3.5). Specifically, the impact of increased premiums can be seen in Figure (3.5a). For the risk-neutral retailer (the rightmost end of the curves), the change in premiums does not have impact on the expected cost. In contrast, for the risk-averse retailer (the leftmost end of the curves) the increased premiums result in significantly higher expected cost. In fact, the impact on expected cost is stronger the more hedging is conducted.

The change in the risk (H2, H3, and H4) can be observed similarly by comparing, the horizontal changes of the risk-neutral retailer, for example. Figures (3.5e) and (3.5f) show that for the price-related input parameters the change in risk strongly depends whether the retailer is risk averse or risk neutral. This can be seen by comparing the horizontal differences between the curves for risk-averse and risk-neutral retailer. As can be seen the risk-averse retailer is almost immune to variability in price-related input parameters while the risk can vary significantly for risk-neutral retailer. More specifically, Figure 3.5f shows that this leads into the curvature of the mean-efficient frontier to be greater when the volatility of the price increases than if it decreases. Also it can be observed that uncertainty in load-related input parameters causes roughly equal amount of risk for both risk-averse and risk-neutral retailers (see Figures 3.5c and 3.5d). This effect can be explained by noting that their future contracts provide a perfect hedge against price changes but cannot capture volume risks. Thus, both retailers need to pay attention to the load-related uncertainties and possibly use swing options or interruptible load contracts to protect against the volume risks. However, the risk-neutral retailer also has to be concerned about the price-related risks that result in greater variability in risk than load related uncertainties.

Further experiments were also run with the correlation being zero (see Figures 3.5b) to analyze how much risk this assumption underestimates compared to the model with positive exponential correlation. Similar tests were also run for the correlation parameter λ and corresponding results were obtained. The difference was significant for the risk-neutral retailer as risk was underestimated by approximately 23%, in absolute terms about 0.3 million EUR, while the effect was less for risk-averse retailer. Thus, including correlation into the analysis was important.

The robustness of the optimum strategies were also evaluated by observing how close the optimal contract portfolio strategy of the original problem, i.e., solution for a given risk aversion, were to the efficient frontiers when the input parameters were changed one at a time. The results suggested that the optimal strategies of the original problem were not sensitive to the changes in the input parameters. These are illustrated also in Figure 3.5.

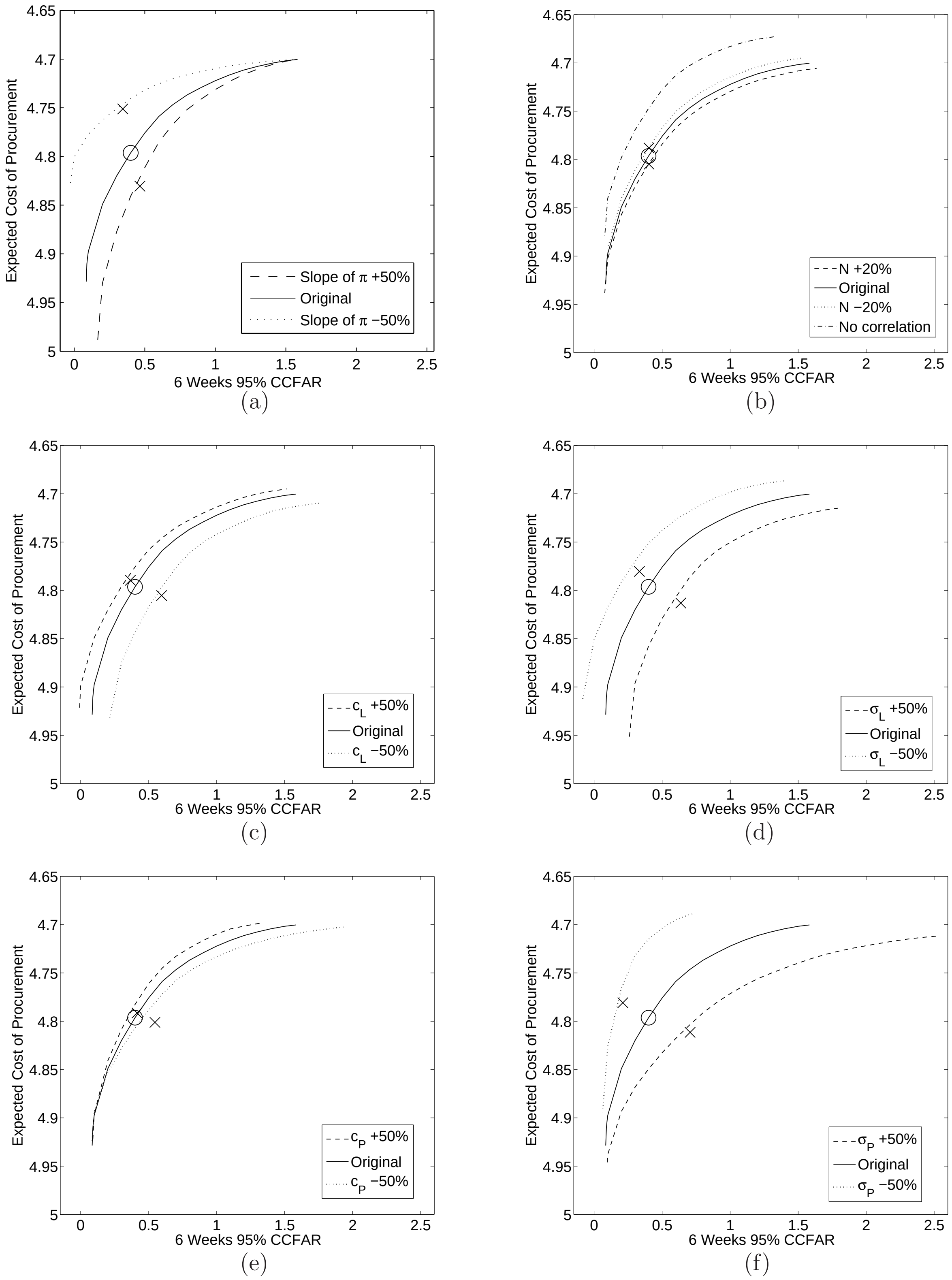


Figure 3.5 Sensitivity of Mean-CCFAR efficient frontier with respect to changes in (a) π, (b) N, (c) c_L, (d) σ_L, (e) c_P, and (f) σ_P

Note, the change in premiums corresponded to the change in the gradient and in volatilities to a parallel shift.

Here the point marked with "O" is the optimal contract portfolio strategy of the original problem, when 6 weeks CCFAR constraint was set to 0.4 million EUR, and is thus on the mean-CCFAR efficient frontier. The points marked with "X" are computed applying the original contract portfolio strategy when the input parameter was 50%[4] higher and lower respectively than originally.

Finally, we conducted experiments to analyze the effects of introducing a risk constraint matrix (with two risk constraints) compared to a single risk constraint. For this purpose we plot the mean-CCFAR efficient surface with respect to four and six weeks 95% CCFAR, which losses relate to an budget of 3.5 and 5.2 million EUR respectively (see Figure 3.6). The risk-neutral retailer is located in this graph close to the corner marked as P_1 at which point the cost of the portfolio is minimized. The risk-averse retailer is close to the extreme corners in the opposite end, for example at point marked as P_2, depending on the required level of risks at six and four weeks.

In Figure 3.6 we also highlight a point A that represents a situation when the expected procurement costs are minimized and a risk constraint only on the six weeks 95% CCFAR is applied at the level of 0.6 million EUR. At this point, the risk at the intermediate four weeks 95% CCFAR is not curtailed. However, by setting an additional constraint for the four weeks 95% CCFAR at the level of 0.4 million EUR it is possible to reduce the four weeks risk by approximately 50% (in absolute terms roughly 0.5 million EUR) while the increase in cost is insignificant being only by 0.1% (in absolute terms only 0.005 million EUR). Consequently, setting constraints concurrently in several time periods can reduce significantly the intermediate period risks, which can be important, for example due to regulatory reasons or if the company is close to financial distress.

3.5. Implications for Electricity Contract Portfolio Management

Our results suggest that the formulated stochastic programming approach can be more efficient in electricity retailer's risk management than periodic optimization or fixed allocation approaches. This result can be attributed to the fact stochastic optimization uses the path dependency of information along individual scenario paths to optimize hedging

[4] For N we used 20% as an increase of 50% would have resulted correlation values that were greater than 1.

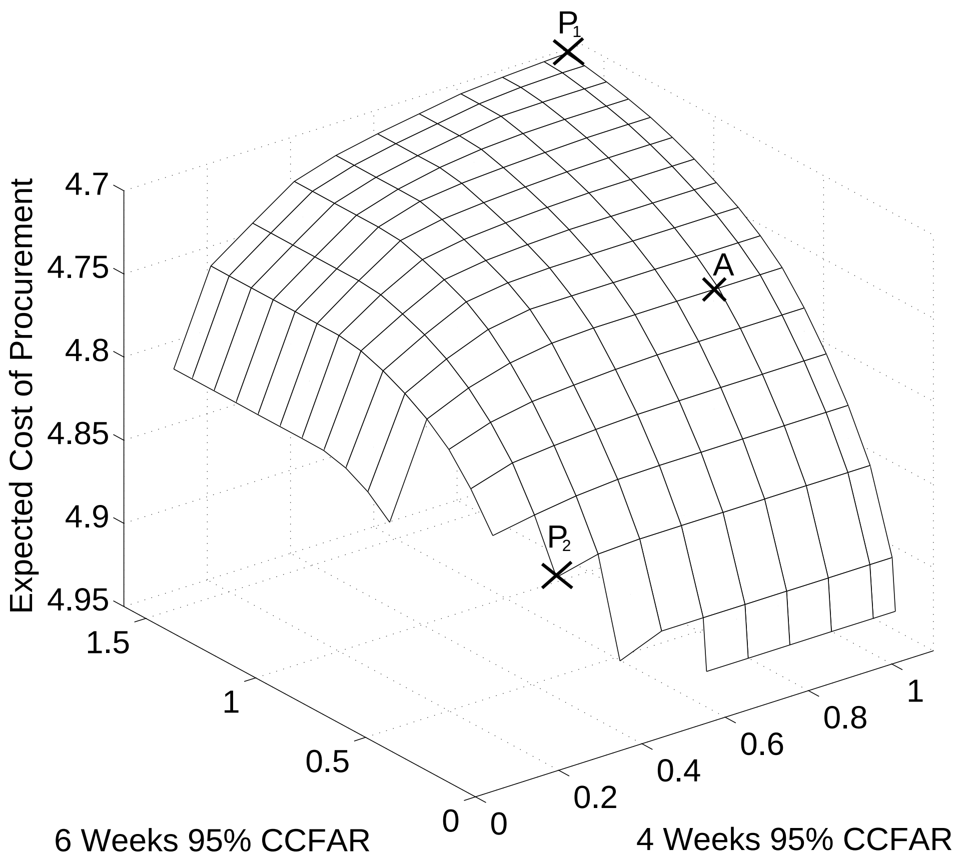


Figure 3.6 **Mean efficient surface with respect to 4 weeks and 6 weeks 95% CCFAR (figures in million EUR)**

in each period. This result is also analogous to the findings of Fleten et al. (2002) who compare the effectiveness of a production and hedging portfolio using dynamic and static models for electricity production.

One of the key insights from the numerical studies is that it is important to incorporate the correlation between spot price and load into the model as correlation increases the probability of the extreme outcomes and hence risks. The results of the experiments also suggest that a risk-neutral retailer would be more concerned about the price-related uncertainties, which result in greater variability in risk, than load related uncertainties. A risk-averse retailer, on the other hand, should estimate carefully the risk premiums that strongly affect the expected cost and should also use derivatives, such as swing contracts, to hedge for load-related uncertainties. Overall the model is relatively robust in that the solutions remain close to the efficient frontier even if there are minor variations in the input parameters.

Our approach also includes CCFAR constraints across several time periods rather than focusing only upon the terminal period. This is important as it allows retailers to keep the cash position in intermediate periods within risk limits for satisfying compliance regulation requirements or above a desired risk level if the company is financially constrained. This risk management across intermediate periods is also important in the methodology, as retailers will continue to operate after the terminal period, and in practice, risk management needs to feed forward continuously. Consequently, it is important in practice to incorporate the risks during the intermediate time periods and to re-run the model for all time periods, rolling forward, when updated information becomes available. The same rationale applies to risk management at different confidence levels, as well.

This research has made contributions to the general direction of methodology. It is possible to integrate additional details, for instance regarding the special market characteristics of the price formation process and load prediction errors, to consider different time specifications, as well as cross-hedging with related markets, most of which present substantial but essentially computational extensions. But, more generally, this research has demonstrated that more accurate results can be achieved in the electricity retailing business by incorporating path-dependencies in the generated scenarios and using multistage evaluation to optimize hedging at intermediate stages. We found that stochastic optimization, combined with a risk constraint matrix framework and allied to the HSS scenario building process provided a viable methodology for this class of problems. Furthermore, it provides insights into the relative sensitivity of risk management parameters to different kinds of market participants in this context.

Chapter 4
Decision Propensities for Power Investment under Carbon Policy Risks

Chapter Summary

Whether companies invest in new power facilities at a particular point in time, or delay, will depend upon the perceived evolution of uncertainties and the decision makers' attitudes to risk and return. With a new and crucial uncertainty emerging through climate change mitigation mechanisms, the propensity to invest will evidently depend upon how each technology is exposed to carbon price risk. We approach this by estimating the cumulative probabilities of investment over time in various technologies as a function of behavioral, policy, financial, and market assumptions. Using a multistage stochastic optimization model with uncertainty in carbon price, we demonstrate that detailed financial analysis with real options and risk constraints can make substantial difference to the investment propensities compared to conventional economic analysis. Further, we show that the effects of different carbon policies and market instruments on these decision propensities depend on the characteristics of the companies, and may induce path-dependent technology choice and market structure evolution. Surprisingly, the analysis suggests that risk-averse investors may, under some circumstances, have a propensity to invest earlier than risk-neutral investors and that accelerated carbon-storage technology adoption rates can sometime encourage investments even in non-fossil technologies.

4.1. Carbon Policy Uncertainty in Power Investment Model

Many regional and state institutions are formulating policies to mitigate global warming that will change the operations of, and investment in, fossil fuel energy facilities. The European Union has had a mandatory cap-and-trade market for carbon dioxide emissions in the power and heavy industry sectors since 2005, with the ambitious post-Kyoto target of at least a 20% reduction by 2020 and much more by 2050, depending upon international accords (BERR 2008, European Commission 2008). Other regions, countries, and states are following (Labatt and White 2007). For decision-making in the electricity sector, carbon price risk and policies present major new uncertainties, the properties of which are quite different from the usual fuel, demand and market risks to which power company managers have become accustomed.

The conventional real option analysis to explore the timing of an investment decision is a well-known theoretical framework (Dixit and Pindyck 1994), with extensions by, inter alia, Santiago and Vakili (2005), Huchzermeier and Loch (2001) and demonstrated value in several practical contexts (e.g., Mittendorf 2004, Tseng and Barz 2002, Meier et al. 2001). Faced with carbon policy risk, real options analysis would be expected to indicate a propensity to delay investments, and this appears to depend upon the technologies (Reedman et al. 2006, Blyth et al. 2007), with nuclear power plants in particular having different optionality properties compared to coal and gas power plants (Roques et al. 2006, Rothwell 2006). This theoretical propensity is appearing in practice, with press comments, such as "Shell has threatened to halt investment....as the uncertainty of this [emissions] policy is too high" (Gribben 2008) whilst Vincent de Rivas, CEO of EDF Energy in the UK comments that "we will not deliver decarbonized electricity without the right signal from carbon prices" (Crooks 2009). To the extent that delays in new power plant construction affect security of supply as well as the achievement of decarbonization, such manifestations are of serious concern to Governments. The purpose of this chapter is therefore to analyze in greater detail how various policies on carbon pricing may affect the investment propensities of power companies and hence further inform policy-making in this respect.

Whilst the straightforward option to delay follows analytically from a risk-neutral decision analysis (Dixit and Pindyck 1994), it is apparent that investment in power generation will exhibit some degree of risk aversion and that modeling this behavioral element may be a delicate process (Ishii and Yan 2004). In some investment decision analyses, real options and risk aversion have been implicitly combined using stochastic dynamic programming and large decision trees with risk-averse utility functions (e.g., Keeney and von Winterfeldt 1991, Smith and Nau 1995, Smith and Mccardle 1998). In practice, however, companies are now more inclined to consider risk as a set of constraints within their financial planning models for investment, using Monte Carlo simulations of the embedded net cash-flow streams to provide risk metrics for cash-flow-at-risk (Froot et al. 1993, Denton et al. 2003, Minton and Schrand 1999, LaGattuta et al. 2001). Companies appear to be increasingly concerned about preserving various financial ratios (e.g., earnings to debt coverage ratios) necessary to maintain their investment grades with the credit rating agencies (Hempstead et al. 2007), and the probability of falling below such critical ratios throughout the life of the project may be their most important articulation of risk. This perspective of a set of intermediate risk constraints throughout the investment planning model effectively precludes stochastic dynamic programming, and in this chapter we develop a new formulation for risk constrained investment analysis based upon multi-stage stochastic optimization.

Optimal power investment models typically assume that new plant will be built whenever there is a positive net present value (Caramis 1982, Schumacher and Sands 2006, Murphy and Smeers 2005, Sen et al. 2006) without real options, or with real options (Reinelt and Keith 2007), yet this would be inadequate to reflect any importance placed upon risk constraints. Furthermore, conventional net present value calculations rarely evaluate financial planning considerations such as optimizing debt exposures. We therefore extend a multistage stochastic optimization model to deal with these risk considerations. Whilst stochastic optimization in this context is not new (Birge and Rose 1995, Birge and Louveaux 1997), we incorporate real options, a new scenario generation approach, risk constraints, and a more detailed level of financial planning into the methodology. This allows us to compute specific cumulative probabilities of investment over the temporal domain, thereby focusing more precisely, than in previous real options analyses, upon the way that policy risk, under various assumptions, affects investment timing. This focus upon relative propensities to invest at particular points in time is a new departure from conventional power investment models, but one that we think is needed to address the delay implications, in the uncertain context of carbon policy.

In more specific terms, whilst it is clear that the mandatory requirement to cover carbon emissions from fossil fuel plants increases their marginal costs by the price of these carbon allowances, how uncertainty in carbon prices affects the investment in different technologies in the presence of real option to postpone the investment has subtle implications. Since costs get passed through into the wholesale markets (Fezzi and Bunn 2008), if the fossil fuel plant, gas and coal, are the marginal price-setters in the market, it may seem that carbon price uncertainty will not affect investment in the carbon emitting plant, if it is financially viable, as much as in the infra marginal, possibly more capital-intensive, non carbon emitting plant, such as nuclear. This then raises the questions of whether risk aversion will have a larger effect on the non-fossil technologies, and how Government policies to reduce risks will affect decision-making in different technologies. If it is apparent that there is a substantial difference in propensities to invest between the risk averse and the risk neutral, and also between the project and equity financed participants, then, apart from the level of carbon prices per se, the associated policy risk will have an effect on market structure evolution through a tendency for investment to be led by dominant incumbents rather than new independent power producers, leading to a less competitive market. This will be further enhanced if the resource-base benefits of a particular portfolio of existing facilities increase the propensity to invest. Finally, and more fundamentally, one might expect that risk aversion would generally tend to increase the propensity to delay. However, if the temporal evolution of risks is perceived as sufficiently increasing, the reverse may happen. We are therefore particularly interested in how carbon policy risk may affect market structure evolution and most of the commentary on the results achieved is developed to provide general insights into this question.

However, in focusing specifically on the impact of carbon policy risk upon the temporal cumulative probability function of investment, we do not seek to address the issue of technology choice. Rather, we envisage a company considering the investment decision in a new power plant of a particular technology accounting for the characteristics of the company, which are not limited to the availability and conditions of the existing assets as in Levi and Nault (2004) but include also carbon policies, financial considerations, and risk attitudes. We analyze in detail how the probability of investment by a particular date would increase or decrease, and how their relative effects emerge. Whilst a general economic perspective might view an industry with homogeneous agents each willing to invest in any technology, we take the observation that the industry is heterogeneous and that, providing an investment is financially attractive, companies will pursue technologies with which they have experience or to which they are strategically attracted perhaps due to the game-theoretic market situation. We do not, therefore, engage in a discussion of whether one technology or another is the most preferred, as, even from an economic perspective, that is so dependent upon fuel and construction assumptions that change rapidly (Milborrow

2008). We do, however, address questions of whether carbon policies and other factors affect different technologies to a relatively different extent. Nor do we address, for the same reason, the issue of the optimal capacity mix for carbon mitigation (Roques et al. 2006, Grubb et al. 2006, Green 2007), except insofar as identifying the effect that an existing technology portfolio might have on a singular new investment. Finally, we take a liberalized market perspective on power investment in that companies will look at each investment as a project, evaluated on its financial merits in the market, distinct from a regulated monopoly that would engage in least cost long-term planning of multiple investments over a long horizon (Caramis 1982). This single investment perspective is therefore quite distinct from the conventional capacity planning models that have been prevalent for many years in the context of aggregate planning, but we believe it is more realistic in a market setting, where incumbents compete with new independent power producers, and more suitable to provide the focus on the specific investment propensities that we are seeking.

The research contributions of the analysis are both reassuring and surprising. First, we show that incorporating financial details together with real options and uncertainty can make significant differences in the evaluations of the investments beyond the basic economic net present value formulation. Thus, we show that capturing the important corporate aspects of behavior is important in the investment modeling. As regards the policy risk exposure, the impacts do vary by technology and financial strength, suggesting that policy risk may affect the evolution of market structure. Larger, financially stronger, and more diversified incumbent players can accommodate policy risks better and are also less likely to postpone their investment decisions than new, project-financed independent power producers, suggesting a tendency for carbon policies to make the markets less competitive. Further, policy variations such as caps, floors, or free emission allocations for new plants do make a difference, again depending upon technology and corporate behavior. The surprises that emerged, however, reinforced the value of accounting for company specific characteristic, as it is clear that in assessing the relative effects of policy risk and instruments, the "devil" is indeed often in the detail. For example, whilst one might expect the risk-averse participants to always invest later than the risk-neutral, we find the opposite occurs for coal if the power sector is quite profitable, or for coal and gas if their cost of capital is relatively low, and just as surprising, that increased price volatility may encourage investment by risk-averse gas generators. We also observe that a breakthrough in carbon capture and storage for coal and gas plants may actually encourage investment in the competing technology, nuclear. We develop the intuition behind these observations in section 4.4, but

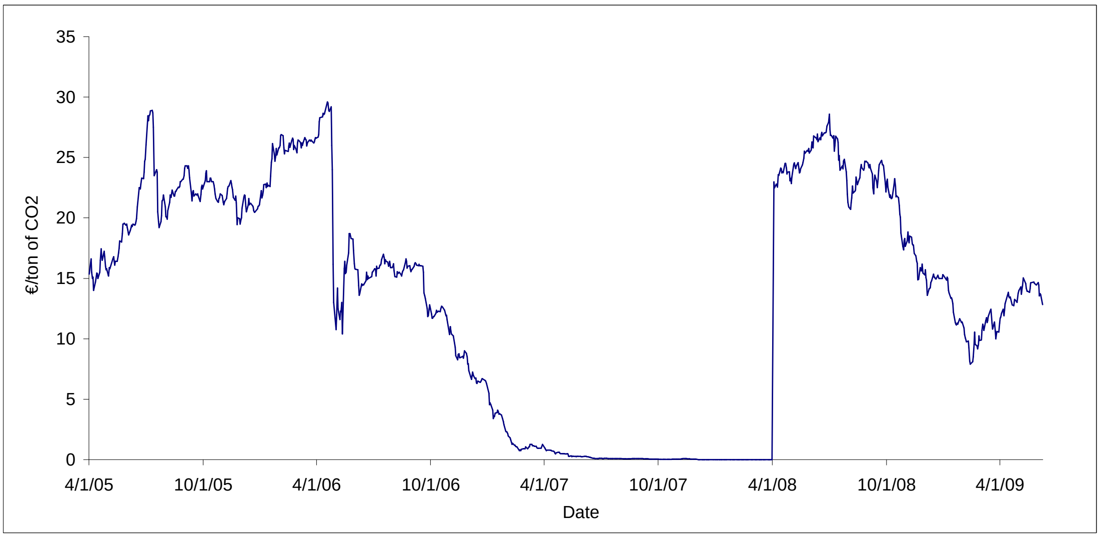


Figure 4.1 Carbon price evolution, European Energy Exchange

such subtle policy-agent interactions would not have become evident without the precise focus of the model.

Figure 1 shows the evolution of carbon spot prices in the EU since the cap-and-trade market for allowances started in 2005. Cap-and-trade markets evolve through stages of cap-setting. The first stage was 2005-2007, and it is clear that within that stage there was considerable volatility with many jumps in the price. Towards the end, the price declined to zero as it was perceived that the cap had been more generous than original market expectations and that there was not really a shortage of allowances in the system. The spot prices rose in the second phase, 2008-2012, initially with belief that EU policy was to be stricter, but since 2009, prices again declined with the economic recession this time mitigating the intended shortage in the market. Policy risk for 2013 and beyond depends upon the tightness of the cap-setting. Uncertainty in the carbon market therefore has stochastic evolution within each phase of cap-setting, and jumps between each phase as new targets get set. The impact of these prices can be substantial. For coal fired generation, each unit increase in the price of carbon per tonne adds about the same amount to the marginal cost of generation, so that in the early months of 2006 and 2008, the marginal cost of coal fired generation was almost doubled because of the carbon allowances. On gas-fired generation, the effect is about half that of coal, so the policy intent is to motivate switching from coal to gas.

The chapter is organized as follows. Section 4.2 formulates the carbon risk investment setting and section 4.3 describes the model. Section 4.4 motivates the experimental propositions and comments upon the results. Section 4.5 concludes.

4.2. Decision Problem of Power Utility

We focus upon the two heavy carbon-emitting technologies, coal and gas, where carbon trading will directly influence operational costs and investment. We also consider a non-fossil capital intensive alternative, nuclear, the properties of which can be generalized to similar facilities such as hydro. A company is considering investment in one facility, in the presence of uncertainties on carbon and electricity prices. The investment decision can be taken immediately or be postponed to await more information regarding the expected future carbon and electricity prices. Once the decision to invest is made, it is followed by a construction period, after which the plant can be taken into operation. In later time periods, a company can also make a decision to retrofit carbon capture and storage (CCS) to coal or gas facilities to reduce its emissions.

Apart from deciding upon the timing of the investments, the company considers how the investments are to be financed. The investments can initially be financed by using full, part, or no debt capital depending on the asset circumstances of the company (see Figure 4.2). Later, the company may decide to pay off some of its debt until finally the remaining debt is paid off at the end of the life time of the plant. The company's cash position is hence dynamic and depends on the revenues received, taxes, debt servicing, and depreciation.

The risks of the investment are the outcomes that result in lower cash positions than if the investment were not made. We assume that the company's objective is to maximize the expected financial net worth of the investment while acknowledging the credit risks throughout the life time of the power plant.

The investment model therefore consists of the following four modules (i) carbon price scenario generation, (ii) electricity price scenario generation, (iii) investment timing, and (iv) risk analysis. The first module takes the expected carbon price trajectory and volatility as an exogenous input, and it is assumed that all agents in the model see this underlying scenario for carbon price evolution. The module converts this basic carbon trajectory into temporal carbon prices in discrete intervals from log-normal distributions with a binomial

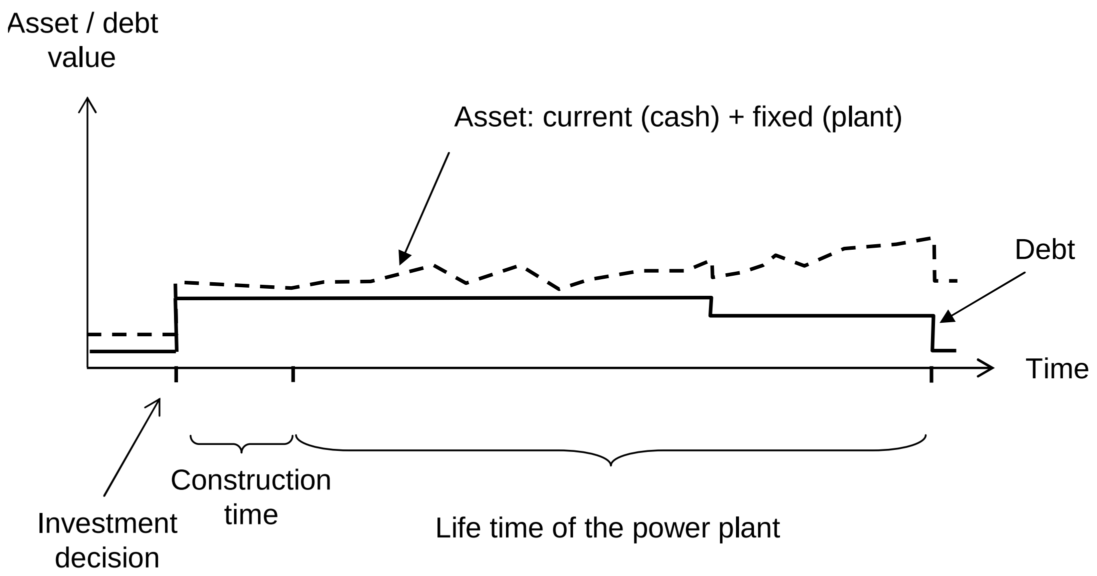


Figure 4.2 **Power plant investment and the value of asset (dashed line) and debt (solid line)**

tree sequential dependence. Thus, there is path dependency in the conditional expectations for carbon prices as perspectives move through the scenario tree. The second module takes exogenous assumptions about fuel prices and the electricity generation profit margin to create, with the addition of the carbon prices at the particular points in the scenario tree, the wholesale electricity prices. These power prices are assumed to be set by the marginal generator, which could be gas or coal depending upon the additional supplement of carbon at particular points (gas uses about half as much carbon allowance as coal for the same unit of output). The third module formulates the investment timing decision as a stochastic optimization problem using the carbon and electricity price scenario tree. For a particular technology, the model computes the optimal time to invest, if at all, under each scenario. Then, the fourth module evaluates the financial risk constraints that are applied for the cash positions. Given the scenario probabilities, and the various financial parameters, the model then allows the computation of the expected net present values, conditional cash-flows-at-risk, and the cumulative probabilities of investment at each of the time intervals.

4.3. Power Investment Model

4.3.1. Generating Carbon Price Scenarios

We represent the uncertain evolution of the carbon price over a finite time horizon $t = 0, ..., T$ using a binomial scenario tree. Each scenario $\mathbf{s^t}$ at time t is a row vector with t

elements. The moves in the tree are given by the binary indicator s_i^t, which is 1 if the move is up, and 0 if the move is down in the tree in period $i = 1, ..., t$ (i.e., all the moves from period 1 until period t). The set of all scenarios at time t is defined as S^t and it consists of 2^t scenarios

$$S^t = \{\mathbf{s^t} | s_i^t \in \{0,1\}, \quad i = 1, ..., t, t = 0, ..., T\}.$$

The unique immediate predecessor of scenario $\mathbf{s^t} \in S^t$ $(t > 0)$ is $b(\mathbf{s^t}) = \mathbf{s^{t-1}} \in S^{t-1}$ such that scenario $\mathbf{s^{t-1}}$ is the $t-1$ subvector of $\mathbf{s^t}$, in other words if $\mathbf{s^t} = [u_1\ u_2\ u_3\ ...\ u_t]$ then $b(\mathbf{s^t}) = [u_1\ u_2\ u_3\ ...\ u_{t-1}]$, also $b^2(\mathbf{s^t}) = b(b(\mathbf{s^t}))$ and so on.

We define

$F^{-1}(m):\ [0,1] \to \mathbb{R}^+$ inverse cumulative log-normal probability distribution for carbon prices,
$f_{bin}(i,t,0.5):\ \{i = 0, ..., t, t = 0, ..., T\} \to [0,1]$ binomial probability distribution,
$\mu_t \in \mathbb{R}^+$ the expected carbon values at time states $t = 0, ..., T$,
$c^e_{\mathbf{s^t}} \in \mathbb{R}^+$ cost of an emission contract to emit one ton of CO_2, $\mathbf{s^t} \in S^t$,
$prob_{\mathbf{s^t}}$ $\in$ [0,1] probability of occurrence of scenario $\mathbf{s^t} \in S^t$, and
q_t $\in$ [0,1] probability of move up in scenario tree at time state $t = 0, ..., T-1$.

The recombining carbon price scenarios are generated from inverse log-normal cumulative probability distribution $F^{-1}(m)$ where points $m \in [0,1]$ are the mid points of the probability masses of binomial distribution $f_{bin}(i,t,0.5)$, $i = 0, ..., t$ (cf. Figure 4.3). The probabilities of moving up at time states $t = 0, ..., T$ in the scenario tree are solved recursively matching the expected carbon prices μ_t

$$\sum_{\mathbf{s^t} \in S^t} prob_{\mathbf{s^t}} c^e_{\mathbf{s^t}} = \mu_t \tag{4.1}$$

$$prob_{\mathbf{s^t}} = \prod_{j=1}^{t} q_j^{s_j^t} (1 - q_j)^{1 - s_j^t}. \tag{4.2}$$

Note, this scenario tree generation approach can be seen as an extension of the "bracket-mean" method for multiple periods where the probabilities are scaled to match the means (Smith 1993, Miller and Rice 1983).

4.3.2. Generating Electricity Price Scenarios

We introduce the following notation to derive the electricity prices:

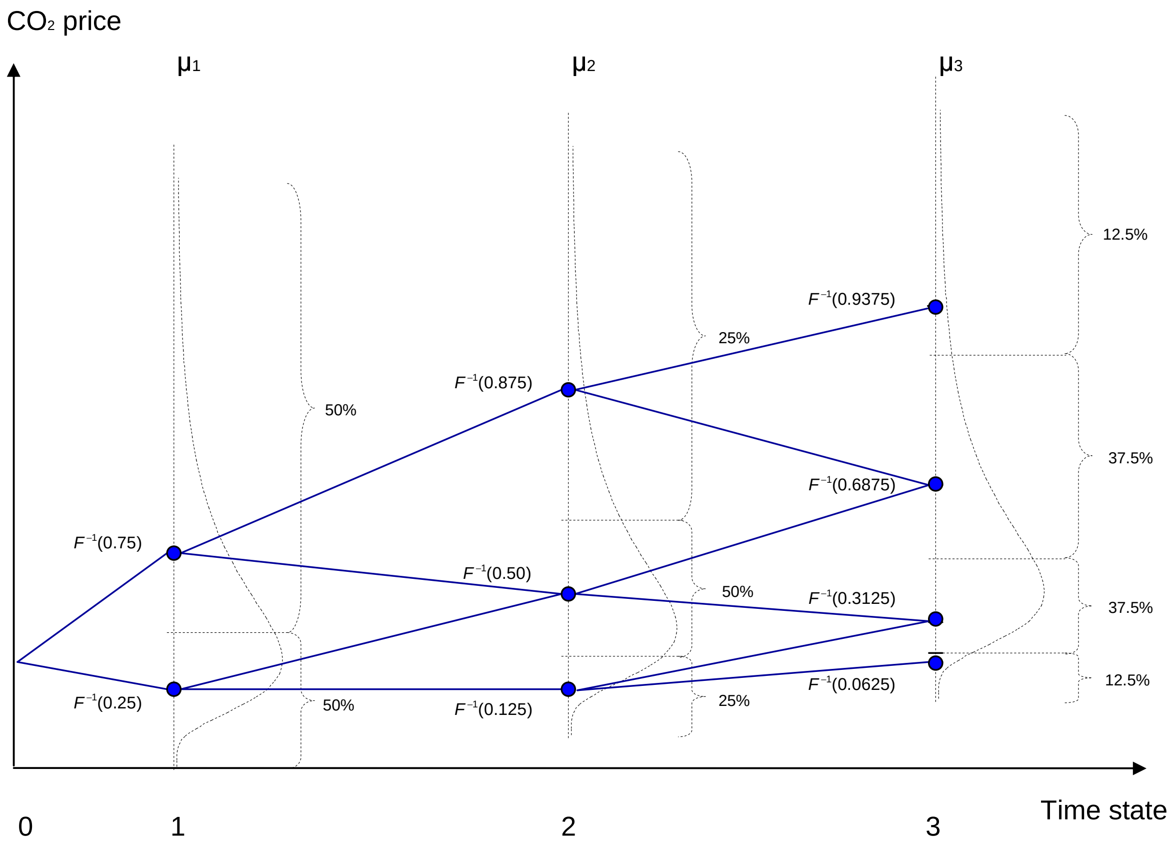


Figure 4.3 **An example of CO_2 price scenario generation from log-normal distribution**

$I = \{g, c\}$ set of price setting plants (g=gas, c=coal),

$p_{\mathbf{s^t}} \in \mathbb{R}^+$ electricity price/MWh, $\mathbf{s^t} \in S^t$,

$y \in \mathbb{R}^+$ profit spread of electricity price over the marginal production cost per MWh,

$e^i \in \mathbb{R}^+, i \in I$ tons of CO_2 emission/MWh, and

$c^{vi} \in \mathbb{R}^+, i \in I$ variable cost of power plant/MWh capacity.

The electricity price is, $\forall \mathbf{s^t} \in S^t \; t = 1, ..., T$

$$p_{\mathbf{s^t}} = y + \max_{i \in I} \left[c^e_{\mathbf{s^t}} e^i + c^{vi} \right]. \tag{4.3}$$

It is based on a simple stack model in which the marginal cost producer is either coal or gas plant depending on the cost of the emission contracts.

4.3.3. Investment Model

The decision variables are (suppressing, for clarity, the superscript i for technology type):

$x_{\mathbf{s^t}} \in \{0, 1\}$ decision to build power plant at time state t, $\mathbf{s^t} \in S^t$,

$x^o_{\mathbf{s^t}} \in \{0,1\}$ decision to retrofit CCS facility at time state, t, $\mathbf{s^t} \in S^t$ (retrofitting assumed to be instantaneous), and

$x^d_{\mathbf{s^t}} \in \mathbb{R}^+$ decision to pay the specified amount debt back at time state t, $\mathbf{s^t} \in S^t$.

Within the investment optimization model, we define the following (again suppressing the superscript i for technology type):

Δ time in years between time states $t = 0, ..., T$,

$v_{\mathbf{s^t}} \in \mathbb{R}^+$ annual revenue from power generation, $\mathbf{s^t} \in S^t$,

$j \in \mathbb{Z}^+$ construction time of a power plant in number of years,

$c^f \in \mathbb{R}^+$ yearly fixed operating cost of power plant,

$u \in [0,1]$ efficiency multiplier of the new plants (compared to the variable costs of pre-existing plant of the same technology in the market),

$c^v \in \mathbb{R}^+$ variable operating cost of power plant/MWh capacity,

$h \in \mathbb{R}^+$ percentage increase in variable cost if CCS built,

$z \in \mathbb{R}^+$ energy production capacity in MWh/year,

$e \in \mathbb{R}^+$ tons of CO_2 emission/MWh of the plant,

$e^o \in \mathbb{R}^+$ reduction in emission in tons of CO_2/MWh when CCS is constructed,

$d_{\mathbf{s^t}} \in \mathbb{R}^+$ one year depreciation of power plant, $\mathbf{s^t} \in S^t$,

$d^o_{\mathbf{s^t}} \in \mathbb{R}^+$ one year depreciation of CCS, $\mathbf{s^t} \in S^t$,

$l \in \mathbb{Z}^+$ lifetime of a power plant in years (including construction time),

$k_{\mathbf{s^t}} \in \mathbb{R}^+$ one year interest payments, $\mathbf{s^t} \in S^t$,

$r^d \in \mathbb{R}^+$ interest rate on debt,

$c \in \mathbb{R}^+$ lump sum investment cost of power plant, and

$c^o \in \mathbb{R}^+$ lump sum investment cost of CCS facility.

The received revenue, interest payment, and depreciation of the investment, we formulate as follows, $\forall \mathbf{s^t} \in S^t$, $t = 1, ..., T$

$$v_{\mathbf{s^t}} = 1_{\mathbb{Z}^+}\left[\sum_{i=1}^{t}(x_{b^i(\mathbf{s^t})})\Delta - j\right]\left[z\left[p_{\mathbf{s^t}} - c^e_{\mathbf{s^t}}(e - x^o_{b(\mathbf{s^t})}e^o) - (1 + x^o_{b(\mathbf{s^t})}h)uc^v\right]^+ - c^f\right] \tag{4.4}$$

$$k_{\mathbf{s^t}} = \left[x_{b(\mathbf{s^t})}c + x^o_{b(\mathbf{s^t})}c^o - \sum_{i=1}^{t} x^d_{b^i(\mathbf{s^t})}\right] r^d \tag{4.5}$$

$$d_{\mathbf{s^t}} = x_{b(\mathbf{s^t})}\frac{c}{l} \tag{4.6}$$

$$d^o_{\mathbf{s^t}} = x^o_{b(\mathbf{s^t})}\frac{c^o}{l - \sum_{i=1}^{t}\left[x_{b^i(\mathbf{s^t})} - x^o_{b^i(\mathbf{s^t})}\right]\Delta}. \tag{4.7}$$

Equation (4.4) represents the revenues. The multiplication by the indicator function ensures that the revenues are obtained only if the power plant is constructed. Note, that (i) the minimum revenues of the power plant is limited to the fixed operating costs of the power plant as it is not operated if variable operating costs are greater than the obtained revenue from the sale of electricity and (ii) the invested plants are of newer generation than the current ones on operation (which set the market price) and therefore gain the inframarginal profit benefit through the efficiency multiplier u. Equation (4.5) keeps track of the interest payments on the outstanding principal. Equations (4.6) and (4.7) provide the depreciation amount for the power plant and the CCS facility by applying a straight-line depreciation method.

We introduce also the following definitions

X^t set of all company's decisions up to time state t,
$a_{\mathbf{s^t}} \in \mathbb{R}^+$ cash position, $\mathbf{s^t} \in S^t$,
$a^0 \in \mathbb{R}^+$ initial amount of available cash,
$r \in \mathbb{R}^+$ opportunity rate of return,
$w \in [0,1]$ company's tax rate, and
$\delta \in [0,...,T]$ final time state when investments can be made.

The overall optimization problem of a firm is therefore as follows

$$\max_{X^T} \frac{\sum_{\mathbf{s^T} \in S^T} prob_{\mathbf{s^T}} a_{\mathbf{s^T}}}{(1+r(1-w))^T} - a^0. \tag{4.8}$$

Subject to cash position constraints, $\forall \mathbf{s^t} \in S^t$

$$a_{\mathbf{s^t}} = \begin{cases} a^0 - x^d_{\mathbf{s^t}} & t=0 \\ a_{b(\mathbf{s^t})}(1+r(1-w))^{\Delta} - x^d_{\mathbf{s^t}} + \\ \sum_{i=0}^{\Delta-1} \Big[(v_{\mathbf{s^t}} - k_{\mathbf{s^t}})(1-w) + (d_{\mathbf{s^t}} + d^o_{\mathbf{s^t}})w\Big](1+r(1-w))^i & t>0 \end{cases} \tag{4.9}$$

decision constraints, $\forall \mathbf{s^t} \in S^t$,

$$x_{\mathbf{s^t}} \geq x_{b(\mathbf{s^t})} \qquad 0 < t \leq \delta \tag{4.10}$$

$$x^o_{\mathbf{s^t}} \geq x^o_{b(\mathbf{s^t})} \qquad 0 < t \leq \delta \tag{4.11}$$

$$x_{\mathbf{s^t}} = x_{b(\mathbf{s^t})} \qquad t > \delta \tag{4.12}$$

$$x^o_{\mathbf{s^t}} \leq x_{\mathbf{s^t}} \qquad t \geq 0 \tag{4.13}$$

$$x^d_{\mathbf{s^t}} \leq x_{\mathbf{s^t}} c + x^o_{\mathbf{s^t}} c^o - \sum_{i=1}^{t} x^d_{b^i(\mathbf{s^t})} \qquad t \geq 0 \qquad (4.14)$$

$$0 = x_{\mathbf{s^T}} c + x^o_{\mathbf{s^T}} c^o - \sum_{i=1}^{T} x^d_{b^i(\mathbf{s^t})} \qquad t = T \qquad (4.15)$$

and integrality constraints, $\forall \mathbf{s^t} \in S^t$, $t = 0, ..., T$

$$x_{\mathbf{s^t}},\ x^o_{\mathbf{s^t}} \in \{0,1\}. \qquad (4.16)$$

Equation (4.8) maximizes the expected net present value (E[NPV]) of the investment. Equation (4.9) balances the cash flows, ensuring that the cash position equals cash inflows and outflows during the years between the time states. Equations (4.10) and (4.11) ensure that once an investment decision is made it remains. Equation (4.12) restricts the investment window when the investment can be done. Equation (4.13) constrains that investment in a CCS facility can be taken only if the investment in the power plant is done. Finally, equations (4.14) and (4.15) ensure that more debt can not be paid back than is initially taken and that it has to be paid back at some point during the investment horizon.

By replacing equation (4.14) with $x^d_{\mathbf{s^t}} = x_{\mathbf{s^t}} c + x^o_{\mathbf{s^t}} c^o - \sum_{i=1}^{t} x^d_{b^i(\mathbf{s^t})}$ the project can be forced to be equity financed. Project financing can be forced by adding an additional constraint $x^d_{\mathbf{s^t}} = 0,\ t < T$. It is straightforward to show with these definitions and the investment equations that if the debt and the opportunity rate of returns are the same, $r^d = r$, the financing structure of the investment does not influence the $E[NPV]$ (consistent with the classic Modigliani and Miller (1958, 1963)). In our stylized framework, however, we envisage the possibility that large incumbent companies have access to lower cost debt and are less risk averse than new entrant independent power companies.

4.3.4. Risk Analysis

To account for the financial risk we use the conditional-cash-flow-at-risk (CCFAR) measure, which is an expected cash-flow measure conditional on a particular lower fractile of the cash position. It is defined similarly to the more general conditional-value-at-risk (e.g., Rockafeller and Uryasev 2000, Uryasev 2000). We introduce the following additional parameters:

$\alpha \in \mathbb{R}^+$ equals cash-flow-at-risk when constraint equation (4.17) is active,

$\beta \in [0,1)$ probability of non-tail event in CCFAR computation,

$\gamma_{\mathbf{s^t}} \in \mathbb{R}^+$ auxiliary variable, and

$\rho \in \mathbb{R}$ risk tolerance measured in CCFAR.

CCFAR is therefore as follows

$$\rho \leq \alpha + \frac{1}{1-\beta} \sum_{\mathbf{s^t} \in S^t} \gamma_{\mathbf{s^t}} \tag{4.17}$$

$$\gamma_{\mathbf{s^t}} \geq prob_{\mathbf{s^t}} (a^0(1+r(1-w))^t - a_{\mathbf{s^t}} - \alpha) \quad \text{and} \quad \gamma_{\mathbf{s^t}} \geq 0. \tag{4.18}$$

These risk constraints can be set for multiple points in time concurrently to manage the risks through out the power plant's life time. This is important as investments in power plants are long-lasting and risk management applied only at the terminal period would overlook the risk of financial distress during the plant's life time.

Using the risk constraints we can define **a Risk-neutral investor** as a decision maker who maximizes return in $E[NPV]$ and **a Risk-averse investor** as a decision maker who minimizes the risk exposure, in CCFAR. This is done by supplementing the objective function equation (4.8) with the CCFAR risk objective $-\lambda\rho$ where the risk aversion factor $\lambda \rightarrow 0^+$ if the function characterizes risk-neutral investor and $\lambda \rightarrow \infty$ if it characterizes a risk-averse investor. Similarly, the model could be specified for a multicriteria decision-maker that would have certain weights for risk and return (Bell et al. 2001).

4.4. Results from Computational Experiments

The experiments were done with an evaluation horizon consisting of $t = 0, ..., 6$ time states, such that investment in a power plant was possible in time states $t = 0, ..., 4$ and for CCS in $t = 4$. Each of the first 4 time periods were 3 years. Periods 5 and 6 varied by technology in order to incorporate the full operating life in the case where the investment is made at the end of period 4. Recall that the focus of this work is not to compare the economic value of different technologies, as in conventional long term capacity planning models, where considerable care has to be taken to evaluate alternatives over the same economic horizons, but rather we are seeking to test the decision maker's propensity to invest in a particular technology against various behavioral and policy assumptions. In a liberalized market with heterogeneous agents, it is perhaps more relevant for Governments to understand

Table 4.1 Data for the experiments

Common parameters		Values		
μ_t	expected carbon prices for period 0,...,4 (£/tons of CO_2)	17, 21, 24, 27, 30		
r	opportunity rate of return or return on excess cash (%)	12		
r^d	interest rate on debt (%)	12		
w	tax rate (%)	38		
y	profit spread of electricity price over the marginal production cost (£/MWh)	5		
$\Delta_1, ..., \Delta_4$	length of time periods 1,2,3,4 (years)	3		
z	effective yearly electricity production capacity (TWh)	7.5		
Power plant dependent parameters		Nuclear	Gas	Coal
j	construction time (years)	6	3	3
l	life time (years)	50	30	40
Δ_5, Δ_6	length of time periods 5 and 6 (years)	28, 28	16, 17	21, 22
μ_t	expected carbon prices for periods 5 and 6 (£)	45, 60	39, 49	41, 53
c	lump sum investment cost of power plant (millions of £)	1500	300	600
c^o	lump sum investment cost of CCS facility (millions of £)	-	200	400
c^f	fixed operating cost (millions of £/ year)	36	16	24
c^v	variable operating cost (£/ MWh)	3	25	12
u	efficiency multiplier of new plant (%)	100	90	85
h	increase in variable cost if CCS facility built (%)	-	50	75
e	CO_2 emissions (tons/MWh)	0	0.35	0.75
e^o	CO_2 emission reductions of CCS (tons/MWh)	-	0.3	0.65

Data is estimated from a number of sources, such as Metz et al. (2005), Blyth et al. (2007), and various industry experts. Note that the construction times assume that all preliminaries are done, such as general permission and licensing, construction plans, grid connection agreements, etc...

the effectiveness of investment incentives upon particular players with their own strategic inclinations, than to envisage an optimal long-term, least-cost market planning solution. We evaluated CCFAR risk constraints on time states $t = 5, 6$, which are the mid and terminal states of the investment, for the cash flow 5% percentiles i.e., $\beta = 0.95$. We did not consider risk constraints in the very beginning, since during the construction and the early periods of operation, investors would still be taking a longer term view on the project. The base case assumptions are represented in Table 4.1. The carbon prices differ in periods 5 and 6 depending on the power plant type because the length of the period, over which the carbon price is linearly interpolated, vary to accommodate the whole operating life time of the concerning power plant type. The formulation presented in equation 4.4 was linearized and the equation 4.9 was adjusted for the different lengths between the time states. The binomial carbon price scenarios were created from log-normal distributions expected values as listed in Table 4.1, and volatilities of 20%.

4.4.1. Specification Relevance

Since an important aspect of our investment model is the incorporation of uncertainties, real options, and financial details (i.e., depreciation, tax, and debt financing), an initial set of experiments were undertaken to calibrate the relevance of these features against a simple, purely economic, net present value evaluation. Figure 4.4 summarises this comparison

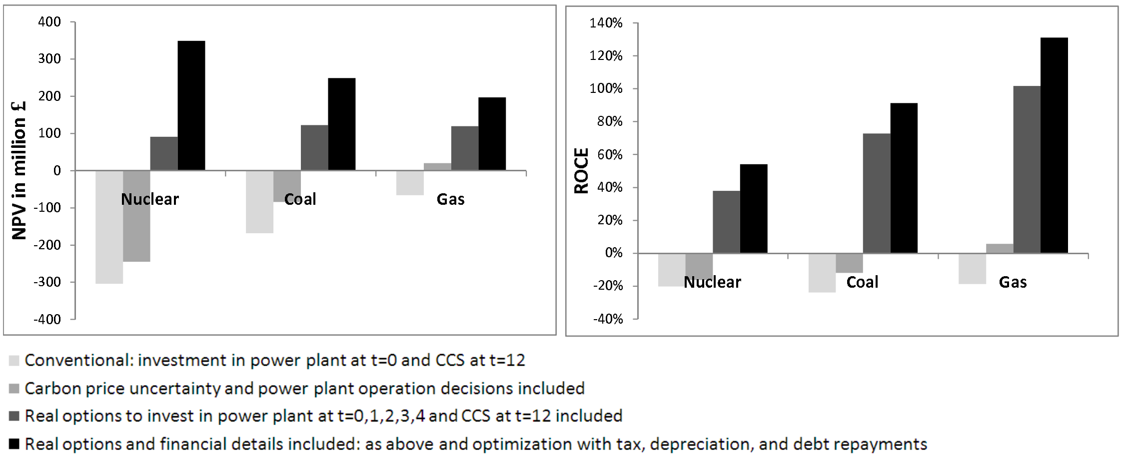
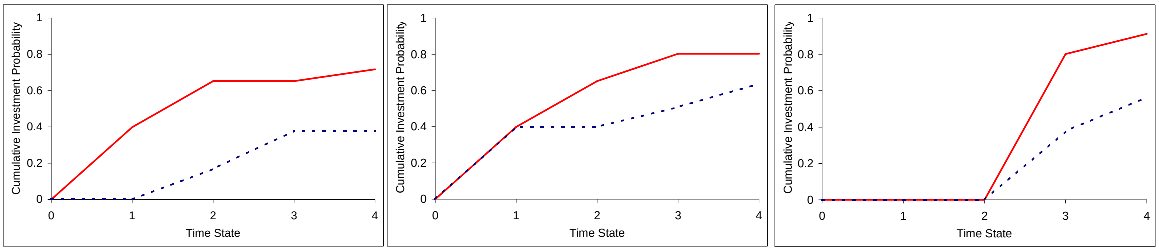


Figure 4.4 Comparison of different investment models

using the base case data. Remarkably, it highlights that all of the power plant investments would be dismissed based on a simple NPV or return on capital expenditure (ROCE) analysis, yet they are all highly profitable when the three behavioral elements are included. The simple NPV assumes that the investment is made and paid for immediately, and that subsequent earning are discounted pre tax. For example, the NPV and ROCE of the nuclear power plant investment change from -£304 million and -20% to £349 million and 54% respectively. Including carbon price uncertainty increases plant's value as in the low carbon and electricity price scenarios losses are reduced by not operating the power plant. Consequently, the maximum loss is limited to the fixed operating costs of the plant (see equation 4.4). The value of the investment increases further when real options to postpone the investment decisions and also the financial planning details are included. The incremental effect of including financial planning details is strong as it increased, for example, the NPV of the nuclear power plant by £258 million and ROCE by 16%. This difference comes from the use of lower discount rate as taxation decreases it (see equation 4.8) and also from the effective use of the depreciation and interest tax shields.

Figure 4.5 shows the investment timing and cumulative investment probabilities (i.e., $\sum_{\mathbf{s^t} \in S^t} prob_{\mathbf{s^t}} x_{\mathbf{s^t}}$ at time t) with and without financial details. As might be expected, the impacts are greater on the more capital intensive projects, nuclear, then coal, then gas. The effects are substantial and so any capacity modeling without considering the financial planing details would underestimate the propensity to invest in the capital intensive projects. They also suggest that selective taxation and depreciation incentives for these technologies could have material benefits, if policy were so disposed.



(a) (b) (c)

Figure 4.5 **Investment decision in (a) nuclear, (b) gas, and (c) coal power plants with financial details (solid line) and without financial details (dashed line)**

It is surprising that including financial details makes such a big difference in the profitability. Earlier work by Bunn et al. (1993) suggested that financial details are second order effects, but that analysis did not incorporate all of the three elements at the same time, nor did it focus more precisely upon the propensity to invest. Thus, it seems that all of the three behavioral specification elements beyond simple economic NPV are important to include simultaneously in precise investment modeling.

4.4.2. Economic Interventions

The economic policy intervention variations were done from the perspectives of risk-neutral and risk-averse investors (e.g., large and small players respectively). We analyze the effects in terms of encouraging (discouraging) investments, i.e. whether the cumulative investment probabilities are higher (lower) and the "gap" in these probabilities between the risk-neutral and risk-averse market participants. We propose the following hypotheses:

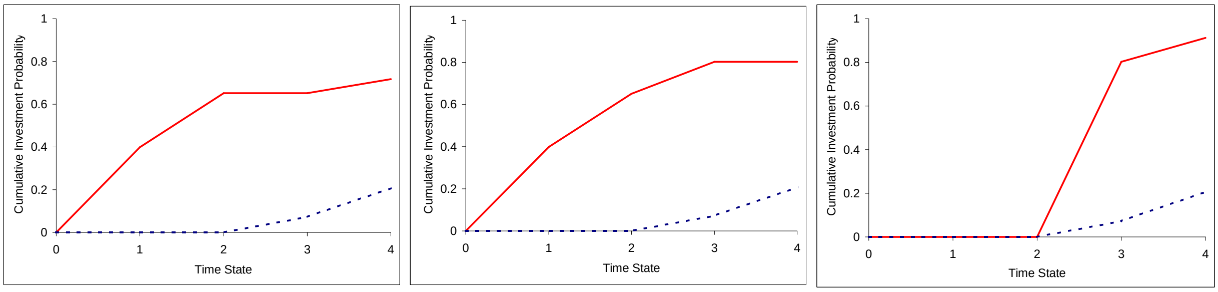
- H1: Enforcing a floor or cap on the carbon price decreases the gap between the investment probability of the risk-neutral and risk-averse investors as the volatility in electricity and carbon prices is reduced. (The desirability of closing the gap between the risk-averse and risk-neutral players could be motivated by policy aspirations to encourage new entrants into the market.)
- H2: Enforcing a floor (cap) on the carbon price encourages (discourages) investments in inframarginal technologies as expected revenues are increased (decreased) because of the pass through of carbon into electricity prices. (Capital intensive investors, e.g., nuclear, may argue that they need a guaranteed level of policy support in order to proceed.)

- H3: Whilst retaining the overall unconditional carbon price expectation, if Governments introduce major carbon policy changes, or shocks, in early time periods, these will discourage the investments of risk-averse investors, as risks in terms of volatility are increased, but encourage the investments of risk-neutral investors as early shocks provide more information regarding the conditional expectations of the carbon price evolution. (This hypothesis is the converse of a belief, often expressed in industry, that Governments should maintain carbon price stability by holding back potential market shocks in the social cost of carbon for longer periods than their emergence would imply.)
- H4: Providing free CO_2 emission allowances during the early periods for new power plants encourages investments as it increases revenues. (This was the motivation in Phase 1 of the EU carbon trading, although it does open up the criticism of providing excessive windfall profits to those who emit most carbon dioxide.)

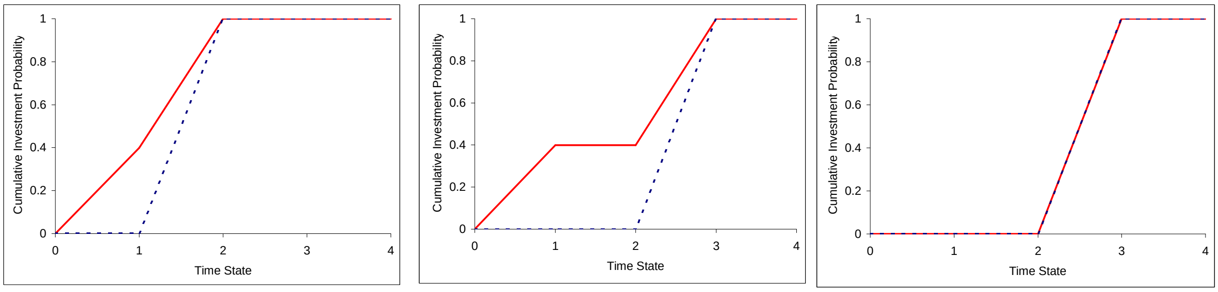
The base case in Figure 4.6 (a) shows that the risk-averse investor postpones the investment decision in all technologies as it can thus (i) learn more about the expected carbon price and invest selectively in cases where risks are the smallest and (ii) have the CCS technology available at $t = 4$. The risk-neutral investor does not invest either at t=0, as it balances between the benefits of investing early to earn revenues and of postponing to (i) learn and eliminate investments in the unprofitable scenarios, (ii) receive higher revenues on later time periods as the carbon and electricity prices are expected to be higher in the future, and (iii) discount the interest payments more heavily (see Figure 4.7).

From the base case we can observe that risk-averse investors' investment propensities are actually the same for all technologies, since the risk-averse investments are only done in the same high carbon and electricity price scenarios when the downside risks are the smallest. More significantly the risk-averse propensities are all very low and substantially below the risk-neutral. Investment is much more likely, therefore, in any technology, by the risk-neutral incumbents. With coal, moreover, both risk-averse and risk-neutral investors prefer to wait for the availability of the CCS technology.

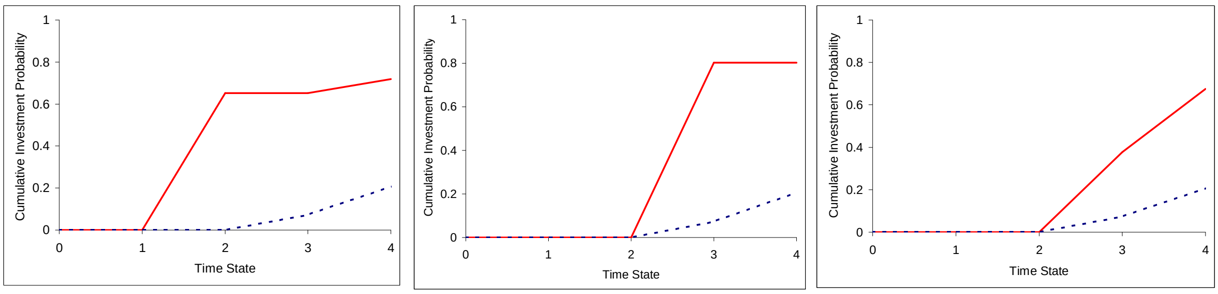
The effects of floors and caps is demonstrated in Figures 4.6 (b) and (c) (for summary of the indications on all of the hypothesis see Table 4.2). With a floor imposed on the carbon price, the propensity of the risk-averse participant to invest increases substantially, and significantly closes the gap with the risk-neutral investor. This is very apparent for the more capital intensive plant. For coal, risk aversion does not make any difference because the risk of low carbon prices is effectively removed and the profitability of the investment



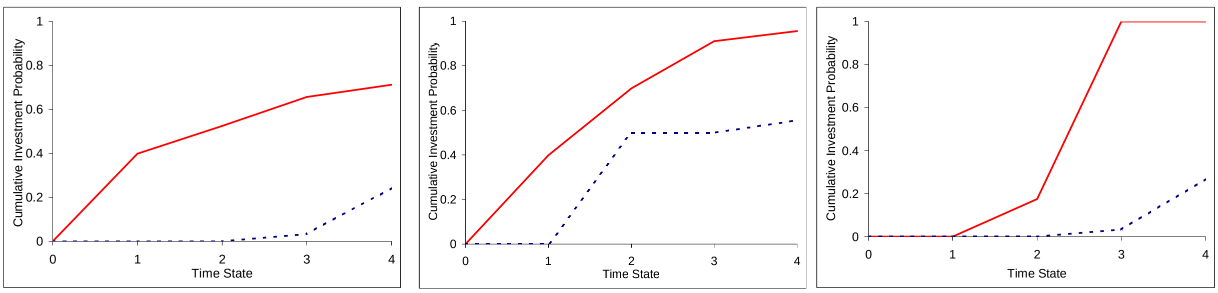
(a)



(b)



(c)



(d)

Figure 4.6 **Investment decision (a) in base case, (b) when a floor (on the level of expected carbon price of the time state) is applied, (c) when a cap (on the level of the expected carbon price of the time state) is applied, and (d) when major policy changes, or shocks, at $t = 2, 4$ are included. The graphs from left to right are for nuclear, gas, and coal power plants where solid line is risk-neutral and dashed line risk-averse decision maker**

can be enhanced by retrofitting the CCS facility. For nuclear, there is only an apparent delay in the first three years. This removal of the corporate discrimination in investment may be more interesting for policy than the overall increased propensity to invest. In

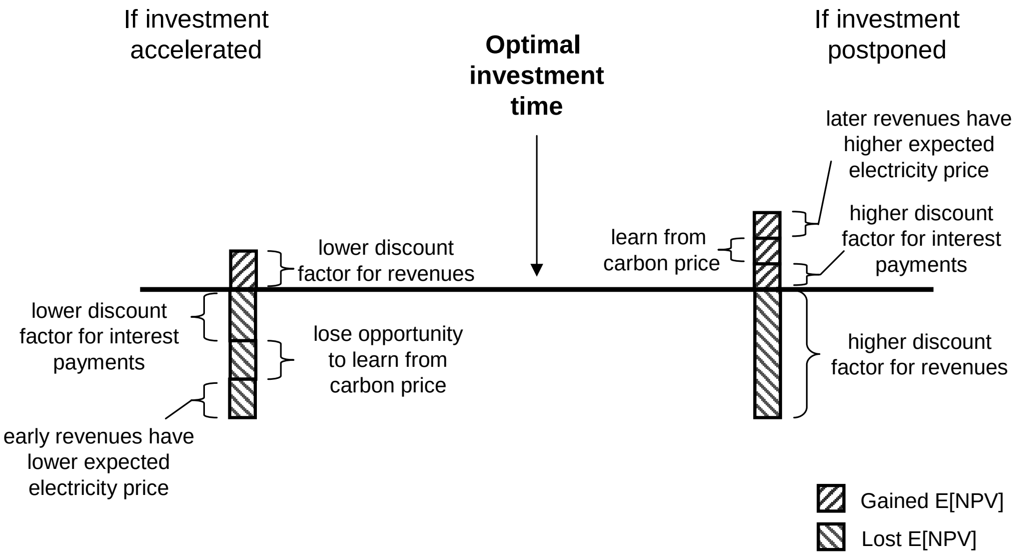


Figure 4.7 Investment timing

contrast, the opposite effects of the cap are most evident for the risk-neutral coal investor whose investment probabilities are reduced. However, the cap did not seem to postpone the investment decisions of the risk-averse investors.

To test the effects of having major policy changes in earlier periods, we included large shocks up and down in the carbon price at time states t=2 and t=4. These shocks were modeled symmetrically, such that the probability to jump up and down was 50% and the jump sizes were 50% of the expected carbon price at t=2 (i.e., £13.5/tons of CO_2). Hence, the expected carbon prices at all time states remained the same as in the base case but the volatility was increased. This is similar to the mean-preserving increase in uncertainty as in the study of Bernanke (1983) in which he shows that an increase in uncertainty increases the option value and decreases the investment propensity due to the possibility of bad news.

As Figure 4.6 (d) shows the hypothesis 3 regarding the shocks is partially refuted. The increase in volatility encourages risk-neutral investments, which contradicts also the result of Bernanke (1983) that an increase in uncertainty decreases the investment propensity. The reason is that the shocks occur during the early periods when the investor can learn from them and make more profitable investments. This is particularly the case in the gas and coal power plant investments as investors have better knowledge whether to build the CCS facility. The early shocks increased the $E[NPV]$ of risk-neutral investor by 12%, 23%, and 36% for nuclear, coal, and gas plants respectively, this can be explained in part, due to an increase in the option value as Bernanke (1983) states. The shocks also substantially increased the propensity for the risk-averse investor in gas. This seems to suggest that it is not in the interests of Governments to "hold back" carbon price shocks from the trading mechanism, if they are beginning to emerge in the scientific awareness and geopolitical processes of global climate change mitigation.

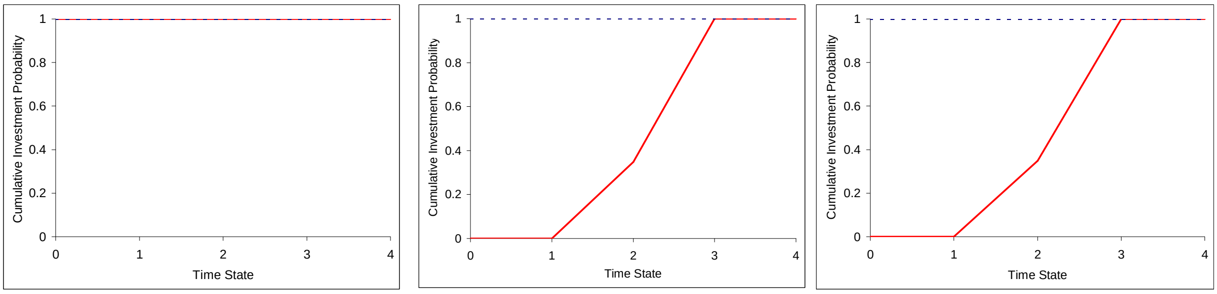
The "free allowances" hypothesis 4 was confirmed in an experiment in which emission contracts equivalent of the emissions of a gas plant were provided for free during the first 4 time states if a power plant was built. This was an effective instrument to encourage risk-neutral investors as all of the investments would be made at t=0 with 100% investment probability. This policy had similar effects on the risk-averse investor's gas investment, but no significant effects on coal or nuclear power plant investments as the acquired windfall profits are smaller fractions of the capital costs and as these plants last 10 to 20 years longer, during which time the same risks exist as without this policy.

4.4.3. Financial and Resource Differentiation

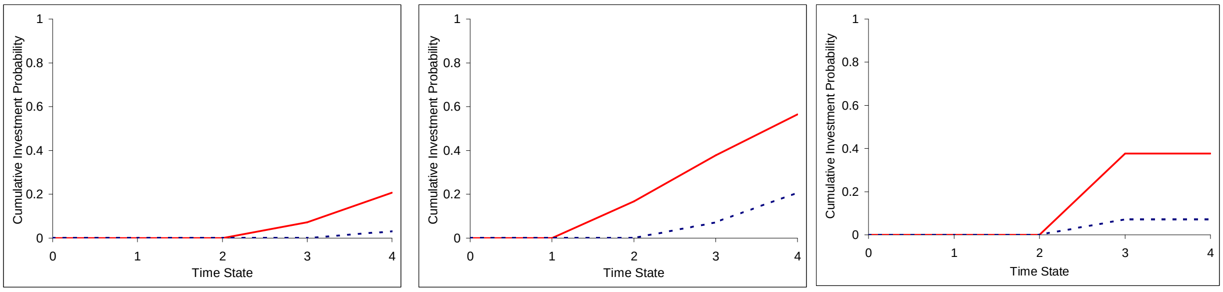
Here we analyze how different financial situations, the availability of alternative opportunities, and an existing portfolio of power plants affect the propensity to invest. We propose the following hypotheses:

- H5: Higher (lower) opportunity rate of return discourages (encourages) investments as the hurdle rate to invest is higher (lower).
- H6: Higher (lower) debt rate discourages (encourages) investments as the investments become less (more) profitable.
- H7: An existing portfolio encourages the investments of a risk-averse investor as the investment can be used to hedge risks.

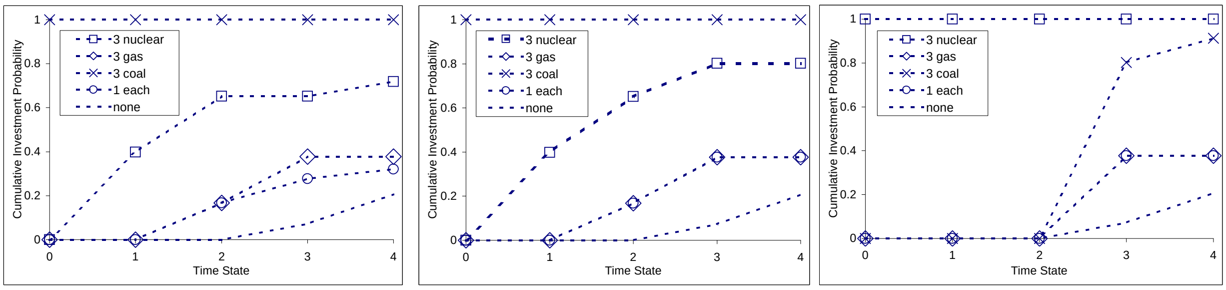
In the investigation of the financial differentiation of the companies, we relax the assumption of having perfectly efficient capitalization and financing, where $r^d = r$. We consider that a financially stronger company may be able to borrow money with a lower debt rate than another even though the opportunity rate of return may still be the same for both. By varying the debt rate and the opportunity rate of return it is possible to characterize a financially stronger and highly capitalized or a financially weaker and strongly leveraged player.



(a)



(b)



(c)

Figure 4.8 **Investment decision when company has (a) a lower opportunity rate of return $r = 0.05$ and (b) a higher debt rate $r^d = 0.2$, and (c) an existing portfolio of powerplants. The graphs from left to right are for nuclear, gas, and coal power plants where solid line is risk-neutral and dashed line risk-averse decision maker**

Figure 4.8 (a) is consistent with the hypothesis 5 in terms of increased investment probabilities following from a lower cost of capital. It also demonstrates that the risk-averse investor may invest before the risk-neutral investor in the gas and coal power plants. This is because risk-neutral investor is willing to take more risk in the tradeoff of a higher E[NPV] as the future carbon and electricity prices are expected to be higher. Note, also that as $r = 5\% < r^d = 12\%$, the financing of the project is optimal using equity rather than debt. If $r = 5\%$ and equity financing is not available and the maximum amount of redeemable debt is limited to the cash proceedings of the investment, the investments of both investors are encouraged but the effects are not as strong as if full equity financing is available. Experiments with $r = 20\%$ confirmed partially the hypothesis 5. The investments of the risk-neutral investor were discouraged as expected, but the investment propensities of the risk-averse investor remained the same as in the base case.

Clearly, higher debt rate discourages investments, as suggested by hypothesis 6. Figure 4.8 (b) shows a financially troubled company, $r^d = 20\%$, where investment was not permitted to be equity financed and the maximum amount of redeemable debt was limited to the cash proceedings of the investment. If equity financing were possible and $r^d = 20\%$ the investments would be fully equity financed and identical to the base case. Lower debt rate, $r^d = 5\%$, confirmed hypothesis 6.

Hypothesis 7 was tested by examining how the investment behavior of the risk-averse incumbent investor differs from a new independent power producer. The existing portfolio consisted either of 3 nuclear power plants, 3 coal power plants, 3 gas power plants, or 1 power plant of each type. As Figure 4.8 (c) illustrates, hypothesis 7 holds. This suggests that the optimal portfolio selection of the risk-averse investor will depend on the pre-existing plants. It also indicates that the emergent portfolios are likely to be more diversified than, for example, in Roques et al. (2008) where pre existing portfolios were not considered and single technology portfolios were found to be optimal in several cases.

In particular, Figure 4.8 (c) shows that the earliest investment in nuclear power plant at $t = 0$ is encouraged if the existing portfolio consists of coal power plants and vice versa. The explanation is that nuclear and coal power plants are a mutual hedge. In low carbon price scenarios coal power plant is the more profitable while in high carbon price scenarios it is the nuclear power plant. If an investment is considered for a gas power plant then an existing portfolio of coal power plants encourages the earliest investment at $t = 0$. This occurs as coal and gas plants can benefit from the fuel switching. In low carbon price scenarios gas plants are the marginal cost producers and in high carbon price it is the coal plants. The reduction in the portfolio risks due to these diversifications are 9%, 6%, and 33% when investments are made for nuclear, coal, and gas plants respectively. What is particulary interesting here is that the diversification strategies appear to be quite selective, and mainly relate to coal and nuclear interactions. A pre-existing, fully diversified portfolio of three different plants is not substantially advantageous, compared to none, for any investment, nor is a portfolio of three gas plants. This suggests an interesting path dependency in the evolution of market structure according to pre-existing asset bases, and that complete diversity may not be a simple answer to risk management. We also experimented with the changes in investment strategies of the risk-neutral investor in the presence of an existing portfolio. As expected, without any risk aversion, the portfolio benefits were immaterial.

The behavioral differentiation of the companies in the market may also stem from the different structural aspects related to the (i) profitability of the electricity generating sector, (ii) adoption rate of the CCS technology, and (iii) availability of the CCS technology. We provide the following hypotheses:

- H8: Harsher (More relaxed) electricity price competition discourages (encourages) investments as the revenues are reduced (increased).
- H9: Faster CCS technology adoption rate discourages investments as the revenues are reduced due to lower carbon and electricity prices.
- H10: Faster CCS technology adoption rate decreases spread between the investment probability of the risk-neutral and risk-averse investors as the volatility of the electricity is reduced.
- H11: Lack (Availability) of the CCS technology discourages (encourages) gas and coal power plant investments as CCS cannot be used to hedge against high carbon prices.

The effects of lower competition in the electricity sector leading to a higher profit margin of $y = £10/MWh$ confirmed hypothesis 8 (see Figure 4.9 (a)). Surprisingly we see that a risk-averse investor invests earlier in coal power plant than the risk-neutral investor. This occurs because the cost of waiting is evidently higher and the risk-averse player is less willing to trade that off against the expected value of waiting. We experimented also with narrower profit margin spreads and the results were consistent with hypothesis 8.

Faster adoption of the CCS technology was tested by including the CCS facility in the marginal production cost plants at time state $t = 5, 6$ (i.e., in the equation 4.3). This decreased the electricity prices at high carbon price scenarios due to the reduction in the emissions e^o but increased the electricity prices at low carbon price scenarios with the additional variable costs of the CCS facility h. These effects are asymmetric and the reductions outweigh the increases, reducing the expected electricity prices. As a result, the $E[NPV]$ of the risk-neutral investors were reduced by 25%, 30%, and 40% for nuclear, coal, and gas power plants respectively. Surprisingly, all the investments are encouraged and the hypothesis 9 refuted (see Figure 4.9 (b)). The explanation for the increase in the investment probability is that the reduction in the volatility of the electricity price allows investors to make better investment decisions. Note, also that the investment strategies of

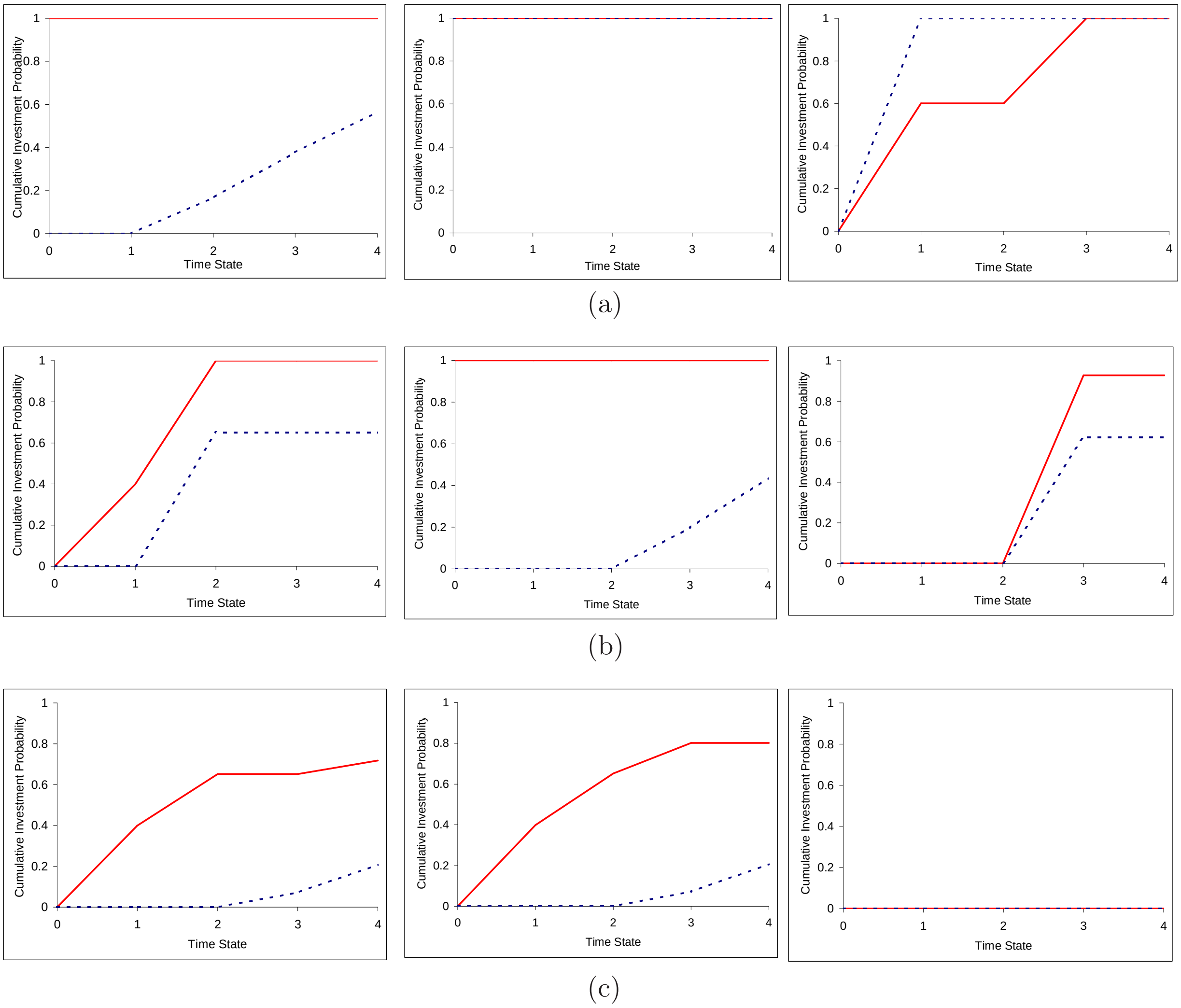


Figure 4.9 **Investment decision when company expects (a) the price competition to be more relaxed y =£10, (b) the CCS technology adoption rate to be faster, and (c) the retrofitting of the CCS facility to be impossible. The graphs from left to right are for nuclear, gas, and coal power plants where solid line is the risk-neutral and dashed line the risk-averse decision maker**

the risk-averse and risk-neutral investors are closer to each other, in the coal and nuclear cases, due to the reduced volatility, hence confirming hypothesis 10.

As suggested by hypothesis 11, investment in the coal power plant without an opportunity to retrofit the CCS facility is discouraged and the investment probability is reduced to 0% (see Figure 4.9 (c)). The investment probability of the gas power plant, on the other hand, is not affected, although the E[NPV] is reduced, e.g., risk-neutral investor loses 25% of its E[NPV]. The reason is that in the higher carbon price scenarios, in which CCS would have been built, existing coal power plants are the marginal cost producers resulting in profits for the gas plants regardless of the availability of the CCS technology. Hence, the CCS facility is not as crucial for the gas plants in short term as it is for the coal power plants.

Table 4.2 Summary of the hypotheses validity

Hypotheses	Validity
H1: Floor and cap decrease the spread between the investment probability of the risk-neutral and risk-averse investors	Confirmed
H2: Floor (cap) encourages (discourages) investments in inframarginal technologies	Partially confirmed
H3: Early carbon policy shocks discourage (encourage) the investments of a risk averse-investor (risk-neutral)	Partially refuted
H4: Providing free emission allowances for new plants encourages investments	Confirmed
H5: Higher (lower) opportunity rate of return discourages (encourages) investments	Partially confirmed
H6: Higher (lower) debt rate discourages (encourages) investments	Confirmed
H7: Portfolio encourages risk-averse investments	Confirmed
H8: Harsher (More relaxed) electricity price competition discourages (encourages) investments	Confirmed
H9: Faster CCS technology adoption rate discourages investments	Refuted
H10: Faster CCS technology adoption rate decreases spread between the investment probability of the risk-neutral and risk-averse investors	Confirmed
H11: Lack (Availability) of CCS technology discourages (encourages) gas and coal power plant investments	Partially confirmed

However, the lack of the CCS technology could eventually force coal power plants out of operation, which after gas plants would be the marginal cost plants and their profitability would then be eroded.

4.5. Implications of Carbon Policy Uncertainty for Power Investments

Overall, the results show that real options, uncertainties, and financial details are crucial in the investment analysis when the capital costs are high and the decisions are irreversible. The more detailed analysis can reveal substantial differences compared to the basic economic net present value evaluation in terms of the value of the investment, the optimal investment timing, and financing structure. Government technology support policies will not, therefore, be properly targeted unless these details are correctly modeled, but they could be very effective. Further, the study demonstrates that pre-existing power plant portfolios are important in the analysis of the risk-averse investor in ways that can be quite subtle. Simple broad diversity may not necessarily help, but specific synergies, such as nuclear and coal, can be very effective in promoting investment. Given heterogeneous market players, the effects of government incentives therefore have path dependent aspects depending upon the financial and resource based characteristics of the market participants.

Thus, carbon policy risks have essentially different effects on the investment propensity of companies with different characteristics. For example, larger financially stronger incumbent players are more likely to be less risk averse and have access to lower costs of capital than new, project-financed independent power producers. Consequently, incumbent players are less likely to use the option to postpone their investment and their propensites to invest are substantially higher. This will eventually lead into a more concentrated and less competitive market structure. Policies to support floors in the carbon price, the early transmission of carbon shocks to the market and supporting innovation in CCS can all help to reduce this tendency to further concentration, but this is unlikely to be reduced substantially without other anti-trust measures.

The experiments shed light on some surprising aspects. For example, a risk-averse decision-maker may, under certain circumstances, invest before a risk-neutral one, even though the overall cumulative investment probability is lower. This can occur, for example, if the market is more profitable for generators. This suggests that in terms of promoting new entrants, allowing the generating business to become more profitable has theoretically attractive, but presumably politically awkward, consequences.

Finally, taking the approach of focusing upon the individual propensities to invest, rather than seeking to analyze market level equilibria, can evidently provide complementary insights into the evolution of industrial organization and the formulation of public policy. Whilst the type of model specified here can become much more complicated, one of the interesting aspects is that within the class of large scale optimization models for the electricity sector, where there has been enormous research in the past 40 years, the approach taken here deliberately avoids seeking to model the full system of generators in a collective long term optimizing way. Rather it focusses upon the effects of incentives on different kinds of players in the market. This seems to be quite relevant in age of liberalized markets, without centralized capacity planning, but it does leave open many aspects of incompleteness, notably strategic inclinations such as first-mover investments, investment signalling, forward contracting, and vertical integration. It also leaves open the endogenous aggregate effects if many agents in the market follow the same incentives. Modeling capacity investment in competitive markets for prescriptive purposes is clearly elusive, as strategic behavior has many drivers, and in a global context even more. Analysis of a particular market might suggest positive economic investment, but if the agents are mainly international companies, even better opportunities could exist elsewhere. Reflecting upon all of these aspects of corporate investment behavior, therefore, clearly suggests that modeling such decision-making in this context has to be very focused on developing insights into particular issues and their relative propensities.

Chapter 5
Value of Flexibility in New Product Development: Impact of Uncertainties about Competition

Chapter Summary

Managerial flexibility, also referred to as real options, can have a significant impact on the value of new product development projects. Several studies have examined how this value depends on the characteristics of the development process. We investigate how competition influences this value using a dynamic programming framework, which values managerial flexibilities accounting for (i) uncertainties in the product performance and market requirements, (ii) different market environments, and (iii) varying strength of competition. Using two dimensions of competition, namely its intensity and the competitors' capabilities, we show that the effect of competition on the value of managerial flexibility is complex. Stronger competition may increase or decrease the value of flexibility, depending on the market environment and whether the available options act as substitutes or complements. We find that - contrary to our expectations - flexibility does not necessarily have greater value in a winner-takes-all market, in which the best-performing product captures the entire market, compared to a shared market, where many products can co-exist and capture market share depending on their relative performance. We demonstrate that the option of delaying a product launch is typically the most valuable when competitors are weak, as the potential for increased profits due to a better-performing product make up for the lost revenues due to the delay. A counter-intuitive result, however, is that under certain conditions, the defer options are actually more valuable in more competitive environments. Our results and insights can help firms understand how managerial flexibility should be explored, depending on the nature and intensity of competition they face.

5.1. Modeling New Product Development

Any new product development (NPD) project is susceptible to uncertainty regarding the success of the development, manifested by the quality of the developed product. Also uncertain are the market expectations, which are influenced by competition. An NPD firm should consider the evolution of both these uncertainties when deciding how much to invest in the development, when to launch the product, or whether to abandon the development completely. Consider, for instance, Microsoft's near-simultaneous announcements of postponing the launch of its Window's Vista operating system and accelerating the launch of the Xbox 360 in late 2005 (Lohr and Flynn 2006). It is likely that these decisions, while being influenced by the success of both development efforts, were also influenced by the fact that Microsoft faces harsher competition in the game console market than in the operating system market. A delayed launch of Vista was less likely to have a negative impact on Microsoft's profitability than a delay in the launch of the Xbox 360.

It is well known that managerial flexibility, also referred to as real options, can have a major impact on the value of NPD projects (Dixit and Pindyck 1994), and how this value depends on the characteristics of the development process in terms of the inherent uncertainty (Huchzermeier and Loch 2001). What is not yet fully known, however, is how competition influences this value. In this chapter, we investigate how the nature and strength of the competition a firm faces influence the value of flexibility in its NPD projects.

We consider the following types of flexibilities: (i) abandon the development, (ii) enhance the development, and (iii) delay the product launch. We differentiate between two types of markets, which we refer to as *winner-takes-all* (WTA) and *shared* markets. In a WTA market, the best-performing product captures the entire market. A shared market can support multiple competing products, but the better-performing products capture a larger share of the market. We consider two dimensions of competition, namely (i) its intensity, measured by the frequency of new product launches, and (ii) the capabilities of the competitors, measured by the magnitude of improvements in their newly launched products.

In order to examine the value of NPD flexibility in different market structures and competitive environments, we develop a stochastic dynamic programming framework for a single firm, expanding the model suggested by Huchzermeier and Loch (2001), who examined how an uncertainty influences the value of NPD flexibility. Our model accounts for (i) uncertainties in the product's performance and market requirements, (ii) different market environments, (iii) varying levels of the strength of competition, and (iv) several types of managerial flexibilities. First, we show that the effect of competition on the value of managerial flexibility is complex, and that stronger competition may increase or decrease the value of flexibility, depending on the nature of the market and whether the available options act as substitutes or complements. Second, although one would expect flexibility to have the greatest value in a WTA market because of the potentially bigger benefits, we find that the opposite can actually be true. Third, we demonstrate that the option to delay a product launch is typically the most valuable when competitors are weak, as the potential for increased profits due to a better-performing product make up for the lost revenues due to the delay. Under certain conditions, however, we show that delay options can actually be more valuable in more competitive environments. This is a counterintuitive result, as a highly competitive environment typically incentivizes firms to try and accelerate their product launches (Miltersen and Schwartz 2004).

Our contributions are fourfold. First, we demonstrate that the nature of competition significantly affects the value of flexibility in NPD. Second, we show how market characteristics impact the way options should be used and when they have the most value, thus advancing the investigation as to the potential uses and misuses of flexibility in firms (Reuer and Tong 2007). Third, we provide tools for screening and reviewing viable options, and help identify when flexibility is the most useful. Fourth, we show that the intensity of competition affects whether options substitute or complement each other.

This chapter is organized as follows. Section 5.2 provides an overview of related work, highlighting some key papers in this area. Sections 5.3 and 5.4 introduce the problem and describe the model. Section 5.5 defines two dimensions of competition. Section 5.6 and 5.7 analyzes the impact of competition on the value of flexibility and examines when the various types of options should be used. Results from an empirical exploration are presented in section 5.8. Section 5.9 concludes and offers some future research directions.

5.2. Approaches for Valuing Flexibility in New Product Development

Several researchers have recently examined the value offered by managerial flexibility in NPD and its relationship with uncertainties. Huchzermeier and Loch (2001) investigate the impact of uncertainty on the value of the option to abandon the project, continue the development, or improve the product. They demonstrate that an increased uncertainty does not necessarily increase the value of flexibility, an interesting result as this was widely assumed to be the case. Their model was revisited by Santiago and Vakili (2005) who show that increased variability enhances the value of flexibility only if the source of uncertainty is the market payoff. We extend the models of Huchzermeier and Loch (2001) and Santiago and Vakili (2005) to enable an analysis of how the nature and intensity of competition affects the value of flexibility in NPD.

Hsu and Schwartz (2008) examine the value created by an option to abandon a two-phased R&D project at the end of each development phase. Their model incorporates uncertainty in the duration, development cost, and quality of the R&D output. Brandao and Dyer (2004) expand this model by allowing the option to abandon to be exercised throughout the development phase. They show that opportunities to further expand the product once the development has been successful can significantly affect the project value and the optimal investment decisions. We add to this line of investigation by introducing an option to delay the launch of the product, which allows for additional product improvements during the delay. We explore the impact of this option on the project value and examine how its use depends on the market environment and the nature of the competition.

Development projects in a WTA market have been explored by Choi (1991) and Weeds (2002). Choi (1991) focuses on the implications of an uncertainty on competitive R&D behavior when the uncertainty stems from a stochastic invention rate. He limits his analysis to two players and considers only one source of uncertainty. In our work, we try to overcome these two limitations. In a similar setting, Weeds (2002) considers two sources of uncertainties, namely the economic uncertainty regarding the future profitability of the project and the technological uncertainty regarding the success of the development. She shows that competition and the race for patents do not necessarily undermine the option to delay an investment, but may actually increase its value. By studying R&D projects in competitive environments, we find under which market conditions such delay options can provide value.

Inspired by the pharmaceutical industry, Schwartz (2004) develops a numerical simulation approach for valuing patent-protected R&D projects. His model accounts for uncertainties in the cost-to-completion and revenues. Miltersen and Schwartz (2004) expand this work and show that competition in R&D shortens the development time and increases the probability of successful development. Their model highlights that for a monopolist, the value of the R&D investment is higher than the aggregate value of the R&D investment for two duopolists and that, on average, the time until the first project is completed is shorter. Miltersen and Schwartz (2007) develop a closed form solution approach for an R&D project with uncertain costs and uncertain time to completion. They compare a monopolist and a duopoly in a WTA setting, with the option to abandon or switch to a different investment level. In this chapter, we generalize these results beyond a duopoly and a patent-protected environment.

Cohen et al. (1996) model a multi-stage development process in which products improve as they proceed from stage to stage. They focus on a deterministic setting and highlight the trade-off between minimizing time-to-market and maximizing the product's performance. We examine a similar trade-off, but also allow for uncertainties in the product development process and the market environment.

Murto and Keppo (2002), Smit and Trigeorgis (2004) highlight the importance of considering competition when valuing flexible projects. Murto and Keppo (2002) use a game theoretic approach to show that competition speeds up the investment when several firms compete for a single investment opportunity. Also, Smit and Trigeorgis (2004) find that the value offered by the option to delay a product's launch may be eliminated in a competitive environment, as competitive forces may provide an incentive to invest early. Interestingly, we find that this is not always the case, and demonstrate that the value offered by flexibility also depends on market characteristics and the nature of competition.

5.3. Decision Problem in New Product Development

We view an NPD project as composed of multiple discrete development stages, like commonly found in pharmaceutical R&D, during which the firm must decide whether to (i) continue development, (ii) abandon it, or if possible, (iii) launch the product into the market. If development is continued, then also the level of the investment has to be decided on, impacting the product's performance. These decisions have to be made in the presence of uncertainties concerning the success of the development and the revenues, which will be obtained once the product is launched. We assume that the firm's overall objective is to maximize the value of the project, measured by its expected net present value (E[NPV]).

The success of the development efforts is captured in the product's *performance*, which is uncertain and measures the desirability of the product, comprising factors such as quality, image, and product features. The product's success in the market depends not only on its performance, driven by the capability of the firm to develop a high-performing product, but also on the competitors' capability to develop a competing product. Therefore, we model the uncertainty in the product's commercial success using the concept of a *required* performance, which can be interpreted as the current state-of-the-art performance of competing products already in the market or expected to be launched soon.

We distinguish among three separate phases, namely (i) initial development, (ii) additional development, and (iii) the market phase. The initial development phase corresponds to the time required to develop a product that can be launched into the market. During the initial development phase, the expected product performance can improve or deteriorate, due to uncertainties in the development process. A firm, however, can also decide to enhance the development, resulting in an increase in the expected product performance. We assume that the duration of this phase is fixed, but the resulting quality of the developed product is not. Therefore, once the initial development is completed, additional development steps can be undertaken, in which the firm can simply continue or enhance development to further improve the product's performance, because the product's performance at the end of the initial development stage could be lower than expected, or it may be possible to include new features or integrate new innovative technologies that have become available (Krankel et al. 2006). In this phase, however, the product's performance can no longer deteriorate, as it is always possible to disregard unsuccessful additional developments and launch the product as currently is. The duration of this phase is not fixed, and terminates when a decision is made to launch the product, or to terminate development altogether. Once the product is launched, the product's performance remains constant at the level achieved in the previous phase. We consider upgrades of products already in the market and new generations of existing products as a new product, with a comparable development process.

During the project, the market requirements also evolve. They can increase due to competitors releasing new products, announcing new technological breakthroughs, or publishing progress reports regarding their development efforts. We assume that market requirements, which we interpreted as state-of-the-art performance of products on the market, does not decrease. Figure 5.1 illustrates the structure of an NPD project, the decisions available to the firm, and the evolution of the product's performance and the market's required performance.

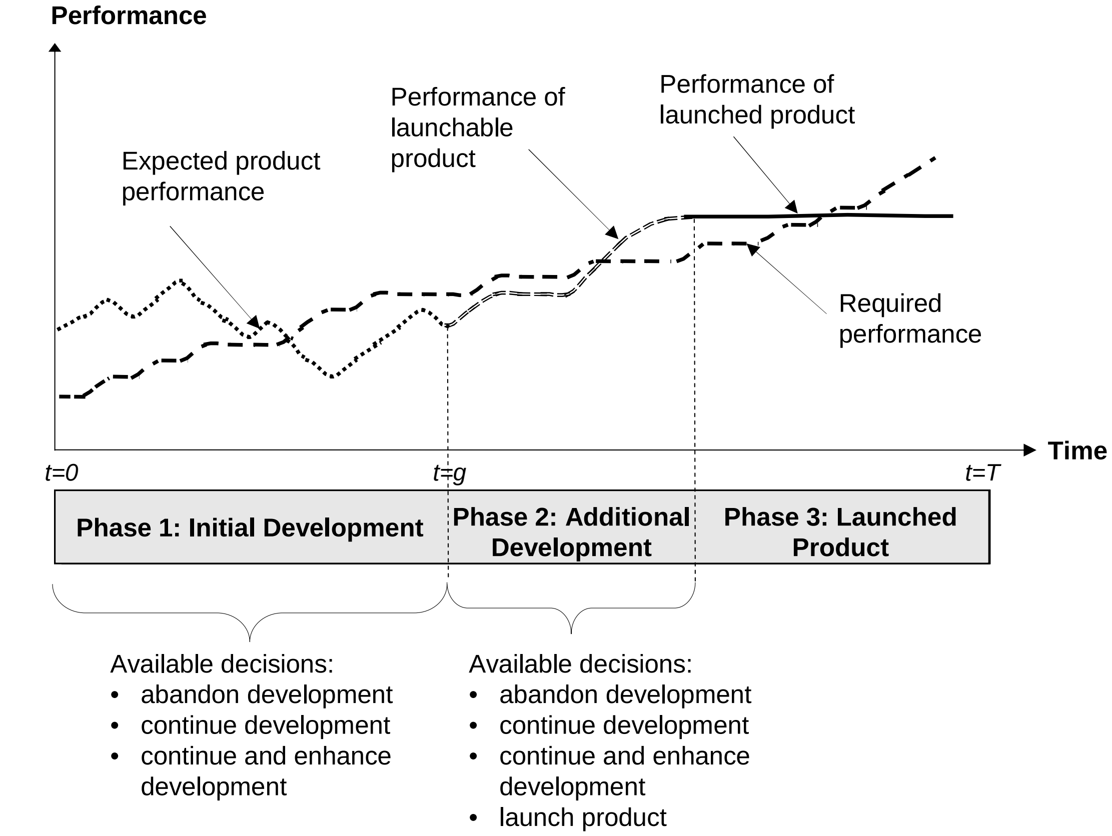


Figure 5.1 **A multi-phase NPD project**

5.4. Model for New Product Development under Uncertainties about Competition

Let a_t denote the decision a firm makes regarding an NPD project at time, t, $t=0,1,...,T$, where

$$a_t \in \begin{cases} \{0,1,2\} & 0 \leq t < g \\ \{0,1,2,3\} & g \leq t < T \\ \{2,3\} & t = T \end{cases}$$

in which $a_t = 0, 1$ or 2 denote the decision to continue, enhance or abandon development, respectively, $a_t = 3$ represents launching the product, available only during the additional development phase, which starts at time g, $0 < g \leq T$.

We define the following parameters

$\pi_0 \in \mathbb{R}$ expected product performance at time g as seen at $t = 0$,

$\pi_t(a_{t-1}) \in \mathbb{R}$ expected product performance at time g as seen at time t, $1 \leq t < g$; or actual performance of launchable or launched product at time t, $g \leq t \leq T$,

$u \in \mathbb{R}^+$ improvement in product performance during each period, $[t, t+1]$, $0 \leq t < T$, with probability q,

$d \in \mathbb{R}^+$ deterioration in product performance during each period $[t, t+1]$, $0 \leq t < g$, with probability $(1-q)$,

$i \in \mathbb{R}^+$ additional improvement in product performance during period $[t, t+1]$, $0 \leq t < T$, if $a_t = 1$,

$\rho_t \in \mathbb{R}$ market's required performance at time t, $0 \leq t \leq T$,

$v \in \mathbb{R}^+$ increase in the market's required performance during each period $[t, t+1]$, $0 \leq t < T$, with probability p, and $(1-p)$ is the probability of market's required performance remaining constant,

$\lambda \in \mathbb{R}^+$ risk free rate per period,

$n_t(a_t) \in \mathbb{R}^+$ development cost incurred at time t, $0 \leq t < T$,

$c_t \in \mathbb{R}^+$ cost of continuing development at time t, $0 \leq t < T$, and

$e_t \in \mathbb{R}^+$ cost of enhancing development at time t, $0 \leq t < T$, with $e_t > c_t$.

Further, we define a two-dimensional state vector $\mathbf{s_t} = [\pi_t, \rho_t]$ that describes the product performance and the market's required performance at time t. The product performance depends on the previous level of performance π_{t-1} and the decision a_t as follows

$$\pi_t = \begin{cases} \pi_{t-1} + u & \text{with probability } q, & \text{if } a_t = 0, & 0 < t \leq T \\ \pi_{t-1} - d & \text{with probability } (1-q), & \text{if } a_t = 0, & 0 < t \leq g \\ \pi_{t-1} & \text{with probability } (1-q), & \text{if } a_t = 0, & g < t \leq T \\ & & & \\ \pi_{t-1} + u + i & \text{with probability } q, & \text{if } a_t = 1, & 0 < t \leq T \\ \pi_{t-1} - d + i & \text{with probability } (1-q), & \text{if } a_t = 1, & 0 < t \leq g \\ \pi_{t-1} + i & \text{with probability } (1-q), & \text{if } a_t = 1, & g < t \leq T \\ & & & \\ 0 & & \text{if } a_t = 2, & 0 < t \leq T \\ & & & \\ \pi_{t-1} & & \text{if } a_t = 3, & g < t \leq T. \end{cases} \tag{5.1}$$

The market's required performance evolves as follows

$$\rho_t = \begin{cases} \rho_{t-1} + v & \text{with probability } p, & 0 \leq t < T \\ \rho_{t-1} & \text{with probability } 1-p, & 0 \leq t < T. \end{cases} \tag{5.2}$$

The development cost is

$$n_t(a_t) = \begin{cases} c_t & \text{if } a_t = 0, & 0 \leq t < T \\ e_t & \text{if } a_t = 1, & 0 \leq t < T \\ 0 & \text{if } a_t \in \{2, 3\}, & 0 \leq t \leq T. \end{cases} \tag{5.3}$$

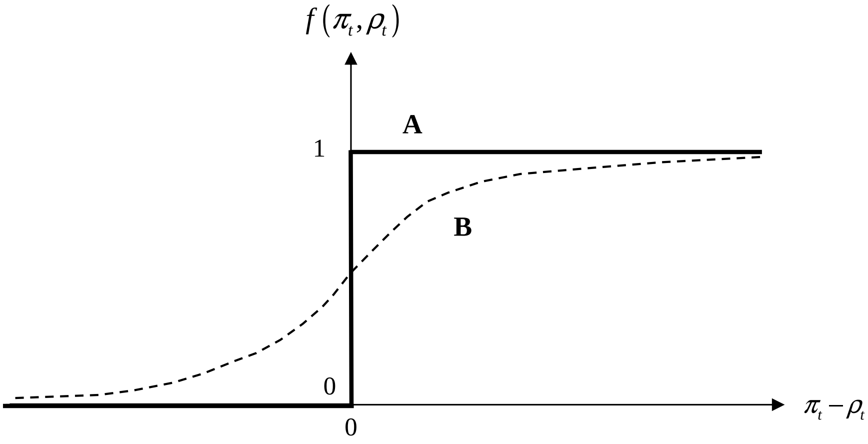


Figure 5.2 Revenue scaling function in winner-takes-all and shared markets

The market payoff, obtained once a product is launched, depends on the product's performance and the required performance at the time of launch and thereafter. The total net revenue can be calculated as

$$\sigma_t(\mathbf{s_t}, a_t) = \begin{cases} 0 & \text{if } a_t \in \{0,1,2\}, \quad 0 \le t \le T \\ \sum_{j=t}^{T} E[(1+\lambda)^{t-j} f(\pi_t, \rho_j) m] & \text{if } a_t = 3, \quad g \le t \le T, \end{cases} \tag{5.4}$$

where $m \in \mathbb{R}^+$ is the maximum possible revenue level, i.e., when capturing the entire market and $f(\pi_t, \rho_t) : \mathbb{R}^2 \to \mathbb{R}$ is a non-decreasing revenue scaling function in $\pi_t - \rho_t$ indicating the impact of competition on revenues. As Huchzermeier and Loch (2001), we use a risk-free discount rate. Alternatively, one may use the weighted average cost of capital. A WTA market is represented with a step function

$$f(\pi_t, \rho_t) = \begin{cases} 1, & \text{if } \pi_t > \rho_t \\ 0, & \text{otherwise} \end{cases} \tag{5.5}$$

as illustrated in Figure 5.2, function A. We represent a shared market with revenue scaling function $f(\pi_t, \rho_t)$ that takes the form of an s-curve, shown by function B in Figure 5.2. These curves are used to reflect that in both shared and WTA markets, performance improvements have little impact on revenues when the product's performance is either very low or very high compared to the market requirements, but small improvements to intermediate performance levels can have a major impact (Huchzermeier and Loch 2001).

The E[NPV] of an NPD project can be maximized using a stochastic dynamic program, solved with backward induction using the following recursive formula

$$\begin{aligned} P_t(\mathbf{s_t}) &= max_{a_t \in \{0,1,2,3\}} \{-n_t(a_t) + \sigma_t(\mathbf{s_t}, a_t) + (1+\lambda)^{-1} \times \\ &\qquad E[P_{t+1}(\mathbf{s_{t+1}}) | \mathbf{s_t}, a_t \in \{0,1\}]\} \qquad 0 \le t < T, \\ P_T(\mathbf{s_T}) &= max_{a_T \in \{2,3\}} \{\sigma_T(\mathbf{s_T}, a_T)\}. \end{aligned} \tag{5.6}$$

5.5. Dimensions of Competition

We measure the strength of competition a firm faces along two dimensions, consistent with the empirical findings of Lunn and Martin (1986), who found that two dimensions of competition are significant when predicting R&D expenditures. Boone (2008) also criticizes existing one-dimensional measures of competition, and argues that since firms are likely to differ in more than one dimension, it may no longer be possible to summarize their market position with a single scalar. He therefore points future research towards the exploration of multi-dimensional competition factors and the trade-off among them. We distinguish between the competition intensity on the one hand, and the competitor's capabilities on the other.

We define the *competition intensity*, CI, as the probability, p, of an increase in the market's required performance in each time period, due to competitors launching new superior products or reporting on successful developments in their NPD programs. Therefore, it measures the frequency with which new products are launched. When CI is close to zero, this can be interpreted either as a lack of competitors, where technological progress is caused by a few firms that dominate the market, or as a lack of innovation. The former is the case, for example, for Microsoft in operating systems development, or for Deep Ocean Engineering, the single key player in the manned deep submersibles market. When CI is close to one, market requirements increase in almost every period. Kodak, for example, faces such a situation, whereby a multitude of competing firms frequently release new digital cameras with improved features.

Other definitions of the competition intensity in the literature include de Figueiredo and Kyle (2006) and Boone (2001). De Figueiredo and Kyle (2006) define the intensity of competition as the number of competing products on the market. In an NPD environment, this would be analogous to the number of product launches. Boone (2001) defines the competition intensity based on the ease with which customers can switch between competing products. Our definition of the competition intensity differs from similar concepts in the literature, in the sense that (i) we view competition as a stochastic process, and therefore model the competition intensity as a probability of competing products being launched, and (ii) we measure it from the perspective of a single firm, instead of defining it as an industry average. The latter is important, as the competition intensity two firms in the same industry might experience differs significantly, depending on the position of each firm in the market.

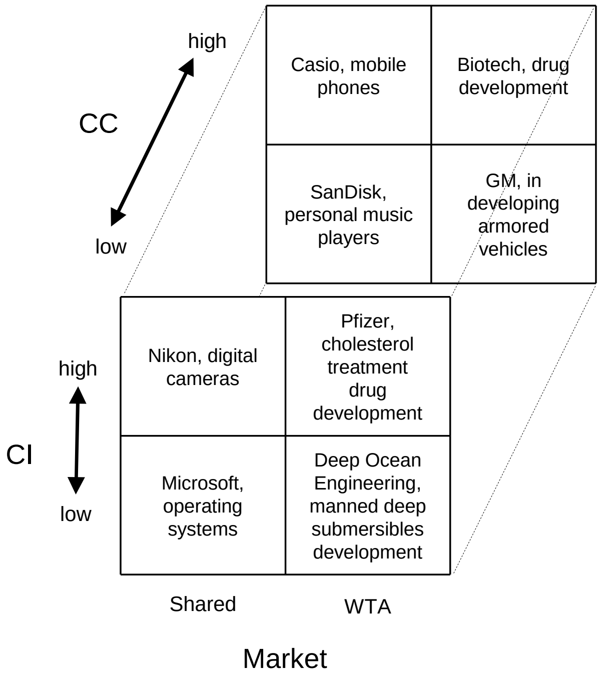


Figure 5.3 **Examples of the level of competition firms face in their industry**

We define the *competitors' capability*, CC, as the increase in the market's required performance relative to the firm's capability to increase the performance of its own product during development, $\frac{v}{u+i}$. When $CC < 1$, competitors are less capable to develop competing products and when $CC > 1$ competitors are more capable. Boeing, for instance, operates in a market with the competitors' capability being approximately equal to one, as Boeing and Airbus seem to be equally capable of raising the bar of required performance. In Figure 5.3 we show several examples of firms in the different competitive environments.

5.6. Competition and Value of Flexibility

In this section we investigate how does competition affect the value of NPD flexibility. For this purpose, we begin with defining NPD flexibility as a set of *options*, $\Omega = \{\epsilon, \delta, \alpha\}$, where ϵ is the enhance option; δ is the option to delay launch; and α is the abandonment option.

Hereafter, we refer to the E[NPV] of a project with all options Ω available as $P(\Omega)$, where $P(\Omega) = P_0(\mathbf{s_0})$, and to the E[NPV] of a project without development options as $P(\emptyset)$, where $P(\emptyset) = P_0(\mathbf{s_0})$ with $a_t = 0$, $0 \leq t < g$ and $a_g = 3$. Further, we refer to the E[NPV] of a project with an option to enhance as $P(\epsilon) = P_0(\mathbf{s_0})$ with $a_t \in \{0, 1\}$, $0 \leq t < g$ and

Table 5.1 Parameters in 2-period Examples

Example 1		Example 2	
Parameter	Value	Parameter	Value
λ, π_0, ρ_0	0	λ, π_0, ρ_0	0
g, q, p, u	1	g, q	1
c_t, t=0,1	1	c_t, t=0,1	1
e_t, t=0,1	2.5	e_t, t=0,1	2.5
i	0.5	i, u, v	0.5
$\sigma_t(\mathbf{s_t}, 3)$	$10(min\{(\pi_t - \rho_t)^+, 1\})$	$\sigma_t(\mathbf{s_t}, 3)$	$10(min\{(\pi_t - \rho_t)^+, 1\})$

$a_g = 3$. Similarly, $P(\delta) = P_0(\mathbf{s_0})$ with $a_t = 0$, $0 \le t < g$, and $a_t \in \{0, 3\}$, $g \le t < T$ and $a_T = 3$. Finally, $P(\alpha) = P_0(\mathbf{s_0})$ with $a_t \in \{0, 2\}$, $0 \le t < g$ and $a_g \in \{2, 3\}$.

We formally define the value of a development option in definition 1. We also establish 5 propositions and hypothesis and provide formal proofs for proposition 1 and 2 in appendix.

Definition 1. *The E[NPV] of a development option $\tau \in \Omega$ is $V(\tau) = P(\tau) - P(\emptyset)$. The E[NPV] of multiple development options $\tau \in \Omega$ and $\varphi \in \Omega$ is $V(\tau, \varphi) = P(\tau, \varphi) - P(\emptyset)$.*

Proposition 1. The value of a project with all options $P(\Omega)$ is a non-increasing function of the competition intensity, CI, and the competitors' capability, CC.

Consider two 2-period examples in Table 5.1, (1) a deterministic ($p = q = 1$) example in which the firm has the option to abandon the project, delay the launch by one period, or enhance development, and (2) a stochastic example ($0 < p < 1$, $q = 1$) with the same options. Figures 5.4 and 5.5 show $P(\Omega)$, $P(\emptyset)$ and $V(\Omega)$ as a function of CC by varying v in example 1, and as a function of CI, based on the second example. Figures 5.4 (a) and 5.5 (a) demonstrate that, as one would expect, $P(\Omega)$ is a non-increasing function of CC and of CI, and that options can significantly increase the project value.

Hypothesis 1. The value of options $V(\Omega)$ can be a non-monotonic function of CI and CC.

Figures 5.4 (b) and 5.5 (b) show the non-monotonic behavior of the option value, $V(\Omega)$, as a function of CI and CC. Figure 5.4 (b) shows that medium values of CC result in flexibility being the most valuable, although this behavior does not always hold for all parameter settings. Similarly, while in Figure 5.5 (b) medium values of CI are correlated with lower flexibility values, this behavior also does not hold in general. Thus, an increase in either the competition intensity or the competitors' capabilities can result in a non-monotonic change in the value of flexibility. This indicates that the impact of competition on the value of managerial flexibility is complex and that the competition is essential to account

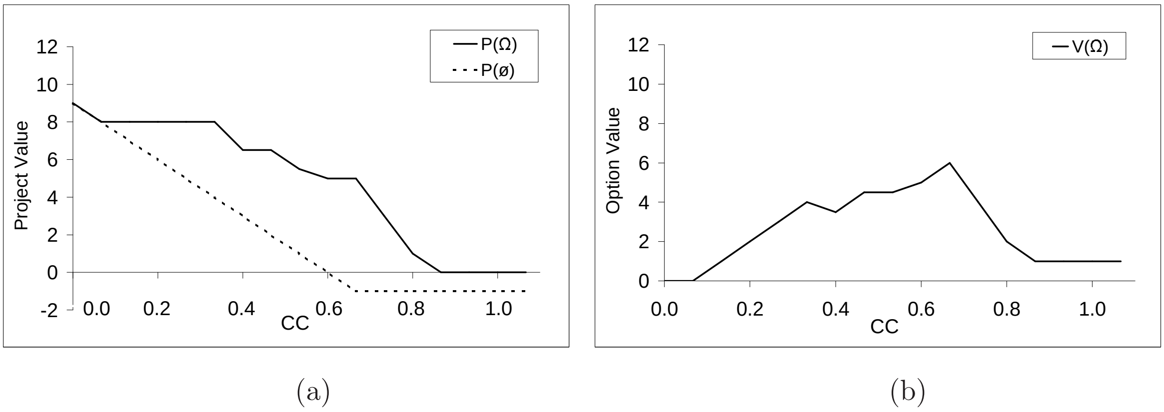


Figure 5.4 **Project and option value as a function of competitors' capability** CC

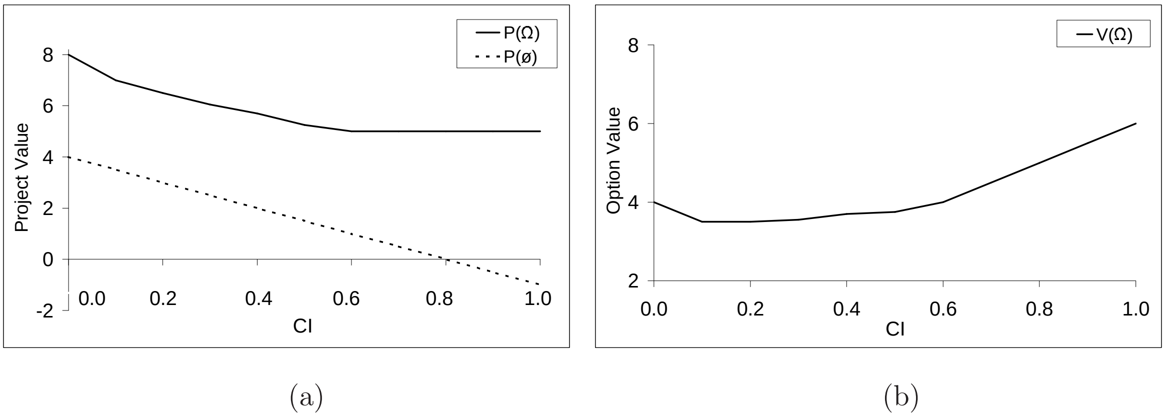


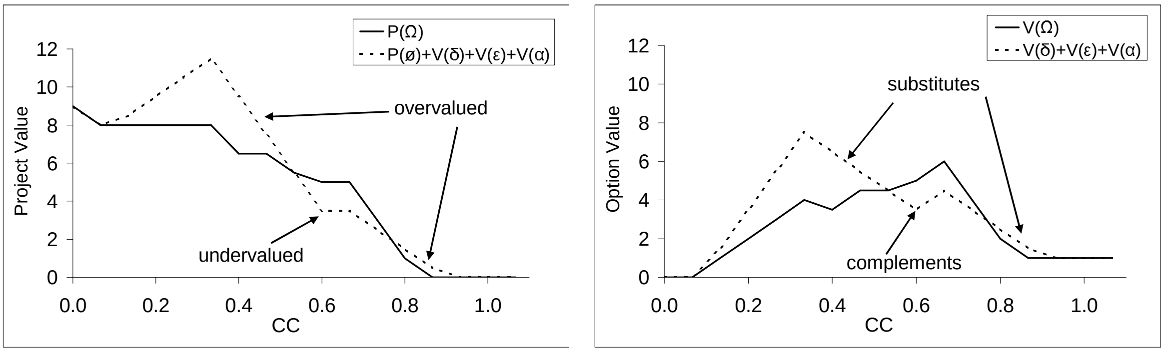
Figure 5.5 **Project and option value as a function of competition intensity** CI

for when managerial flexibilities are valued. Santiago and Vakili (2005) also observe a non-monotonic behavior of option values when uncertainty in the development or market requirement is increased.

Definition 2. *Development options $\tau, \varphi \in \Omega$ are **substitutes** if $V(\tau,\varphi) < V(\tau) + V(\varphi)$, **additive** if $V(\tau,\varphi) = V(\tau) + V(\varphi)$, and **complements** if $V(\tau,\varphi) > V(\tau) + V(\varphi)$.*

Proposition 2. *If development options τ and φ are substitutes or complements then $P(\tau,\varphi) \neq P(\emptyset) + V(\tau) + V(\varphi)$.*

According to Proposition 2, valuing a project and its options separately can result in over- or underestimating $P(\Omega)$, if the development options are substitutes or complements, respectively. Therefore, any project should be valued together with the complete set of options available during development. The importance of properly accounting for the interactions among the options and the valuation errors from ignoring certain options has



(a) (b)

Figure 5.6 Project and option value when not considering options interactions

Table 5.2 Parameters in 3-period examples

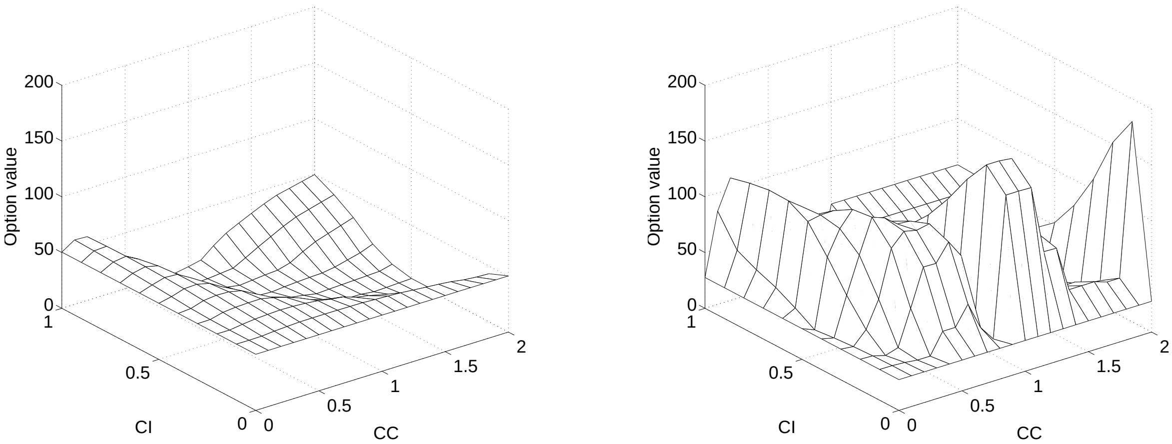
Example 3		Example 4	
Parameter	Value	Parameter	Value
g	2	g	2
c_t, t=0,1,2	13, 50, 5	c_t, t=0,1,2	13, 50, 5
e_t, t=0,1,2	39, 150, 30	e_t, t=0,1,2	39, 150, 30
λ	0.1	λ	0.1
q	0.8	q	0.5
m	100	m	25
$\pi_0 - \rho_0$	1	$\pi_0 - \rho_0$	1
u, d, i	0.5	u, d, i	1

been discussed extensively by Trigeorgis (1993) and Wang and de Neufville (2004). In what follows, we investigate the factors that influence these interactions.

Hypothesis 2. ***CC*** **and** ***CI*** **influence whether options are substitutes or complements.**

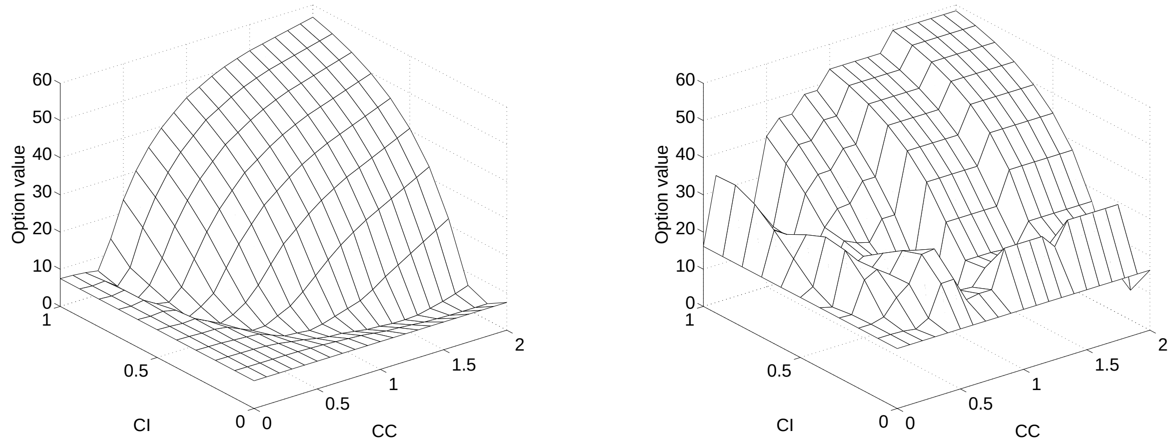
Figure 5.6 shows that $P(\emptyset) + V(\alpha) + V(\delta) + V(\epsilon)$ can differ from $P(\Omega)$, depending on the interactions. In this example, as CC increases, the interaction among the options changes: they are substitutes at lower competition levels, then complements, and again substitutes. This insight has importance for practice, because if options are substitutes then the firm may be able to save resources by planning, preparing, and investing in only a subset of the options, while if the options are complements they should all be invested in. Because the complementarity of the options depends on the competitive environment, the strategic use of flexibility in NPD is a factor of the intensity of competition and the capabilities of the competitors.

Hypothesis 3. **$V(\Omega)$ is not always higher in a WTA market setting than in a shared market setting.**



(a) (b)

Figure 5.7 The value of options $V(\Omega)$ in a 3-period setting in (a) shared market and (b) WTA market



(a) (b)

Figure 5.8 The value of options $V(\Omega)$ in a 3-period setting in (a) shared market and (b) WTA market

Figures 5.7 and 5.8 are generated using a 3-period model, increasing competition intensity, CI, from 0 to 1 by varying parameter p and competitors' capability, CC, from 0 to 2 by varying parameter v, with other parameter settings as in Table 5.2 in Examples 3 and 4 respectively. The market revenue scaling function we represent using a piecewise linear function

$$f\left(\pi_t, \rho_t\right) = min\left\{\left[\frac{(\pi_t - \rho_t - \underline{\Delta})}{\overline{\Delta} - \underline{\Delta}}\right]^+, 1\right\} \tag{5.7}$$

where $\underline{\Delta}$ is the minimum performance level relative to the market requirements, below which no one purchases the product (Adner and Levinthal 2001) and $\overline{\Delta}$ is the maximum

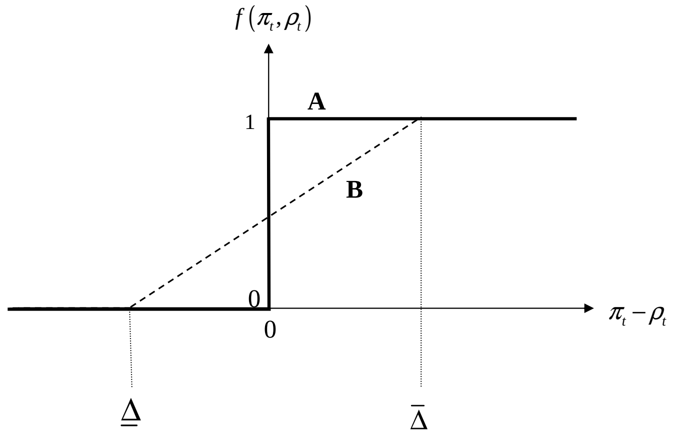
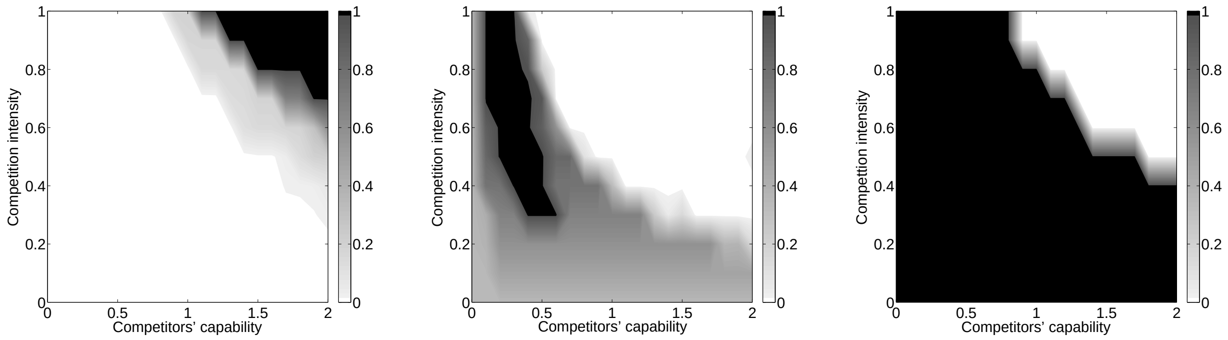


Figure 5.9 **Revenue scaling function for winner-takes-all (A) and shared (B) markets**

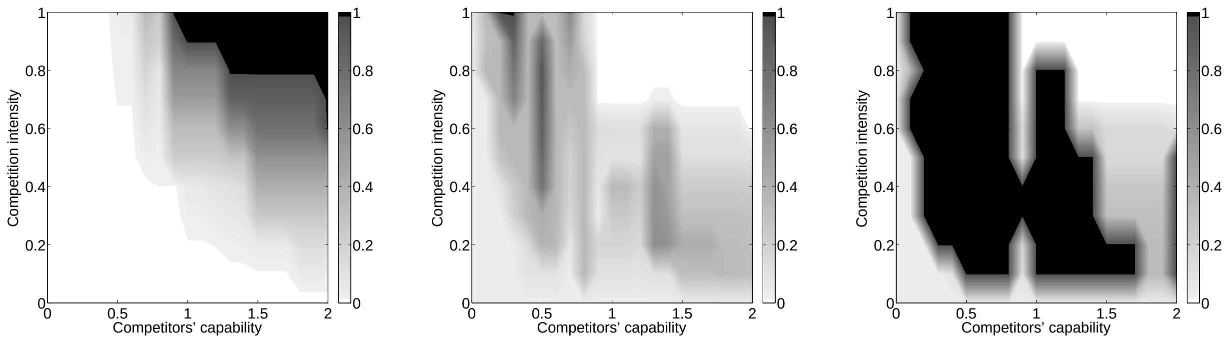
performance level relative to the market requirements, above which maximum revenues are received, $\underline{\Delta} \leq \overline{\Delta}$. Adner and Levinthal (2001) clarify that while there might not always be a maximum limit boundary to the functionality that a consumer is willing to accept, it is reasonable to assume that there is a decreasing willingness to pay for improvements beyond their requirements, to the point that firms cannot extract any meaningful premium for further improvements. If the interval between $\overline{\Delta} - \underline{\Delta}$ is narrow, the market is closer to a WTA market. Hence, the market structure of the product dictates the parameters $\underline{\Delta}$ and $\overline{\Delta}$. The revenue scaling function for a WTA and shared market are shown in Figure 5.9. In the shared market we used the parameters $\underline{\Delta} = -3$ and $\overline{\Delta} = 3$ and in winner-takes-all market $\underline{\Delta} = \overline{\Delta} = 0$. The total net revenue if the product is launched is calculated over 20 additional periods when market's requirements evolved according to its stochastic process.

Figure 5.7 (a) presents $V(\Omega)$, the value of flexibility, in a shared market and Figure 5.7 (b) presents $V(\Omega)$ in a WTA market. First, these figures illustrate Hypothesis 1 by showing the non-monotonicity of $V(\Omega)$ as a function of both dimensions of competition. In fact, the behavior of the value of flexibility as a function of the strength of competition can be quite erratic, as can be seen in Figure 5.7 (b). Second, the value of flexibility can be highest when competition is weak, (Figure 5.7 (a)), medium (Figure 5.7 (b)), or strong (Figures 5.8 (a) and 5.8 (b)). Third, although we expected that options would be more valuable in a WTA market setting as they can be used to stretch the product's performance beyond the market requirements and therefore increase revenues from zero to its maximum possible level, while in a shared market their effect only marginally increases revenue, this is not always the case. This can be seen comparing option values in Figures 5.7 (a) and 5.7 (b) when $CI = 0$ or $CC = 0$.



(a) (b) (c)

Figure 5.10 **Probability of (a) abandoning product, (b) delaying launch, (c) enhancing product development, at least once during the development time, in a shared market**



(a) (b) (c)

Figure 5.11 **Probability of (a) abandoning product, (b) delaying launch, (c) enhancing product development, at least once during the development time, in a WTA market**

5.7. Competition and Strategic Use of Flexibility

Next, we examine how the strength of competition affects which options are likely to be exercised by the firm. Following a general discussion formalized in Observation 1, we examine the effect of competition on each of the options separately, in Observation 2 for the abandonment, in Observation 3 for the delay, and in Observation 4 for the enhancement option.

Table 5.3 **Parameters in 3-period factorial experiment**

Parameter	Value
λ	$\{0.05, 0.1\}$
q	$\{0, 1\}$
m	$\{25, 100\}$
$\pi_0 - \rho_0$	$\{0, 1\}$
u, d, i	$\{0.5, 1\}$

Observation 1.The optimal exercise of development options depends on the market type, the competition intensity CI, and the competitors' capability CC.

We confirmed this in the 3-period model. Figures 5.10 and 5.11 represent the probability of the development options being used in the optimal NPD strategy as a function of the competition intensity and the competitors' capability, in the 3-period example described in Table 5.2 in Example 3. The probabilities are calculated by dividing the number of scenarios in which the corresponding decision was made by the number of overall scenarios. The darker area represents a higher probability of the option being used. Figures 5.10 and 5.11 illustrate (i) that the use of the options is not symmetric in the two dimensions of competition and (ii) the competition intensity, the competitors' capabilities, and the market type affect the way product development options are used. We confirmed this also conducting full factorial experiment with respect to q, λ, m, $\pi_0 - \rho_0$, $u = d = i$ for the values provided in Table 5.3.

From the patterns observed in Figures 5.10 and 5.11, the interactions among the options are clearly visible. The darker area in Figures 5.10 (a) and 5.11 (a) corresponds to the lighter areas in Figures 5.10 (b), 5.10 (c) and 5.11 (b), 5.11 (c), indicating that abandonment serves as a substitute to the enhance and delay options, which complement each other.

Observation 2. Abandonment is used more frequently in a WTA than in a shared market.

Figures 5.10 (a) and 5.11 (a) demonstrate that the abandonment option is used more often in a WTA than in a shared market, which full factorial experiment confirms consistently over all experiments. This result is quite intuitive, as a firm lagging significantly behind its competitors in a WTA market is not likely to receive any payoff, making abandoning the development a sensible option.

Observation 3. Delaying the product launch is useful when the firm can maintain or improve its performance level relative to the market's requirements, for instance when $CC \leq 1$ or $CI \leq q$.

Delaying the product launch option provides an opportunity to improve an otherwise unfavorable developed product. This option is useful when competition is not very strong, allowing for the firm to catch up. Figures 5.10 (b) and 5.11 (b), as well as factorial tests, confirm this. However, delaying the product launch is not necessarily the most useful when

Table 5.4 Companies and their products considered in the empirical example

Product	Company
Operating system	Apple, Microsoft, Red Hat, Canonical, IBM, HP-UX, Sun
Game console	Microsoft, Sony, Nintendo
Mobile phone	Nokia, Casio, Motorola, Samsung, LG Electronics, Sony Ericsson, BenQ-Siemens
Digital camera	Canon, Sony, Casio, Kodak, Fuji, Nikon, Olympus, HP
Airliner	Airbus, Boeing
Desktop computer	Apple, Dell, HP, Gateway (Acer), Toshiba, Lenovo (IBM)
Personal music player	Apple, SanDisk
LCD TV	Sony, Sharp, Philips, Samsung, Westinghouse
Anti-virus software	McAfee, Symantec, Trend Micro, Panda Software, CA

there is no competition, i.e., when $CC = CI = 0$, as Figures 5.10 and 5.11 (b) illustrate. If, for instance, the product's expected performance is initially higher than the market's requirements, $\pi_0 > \rho_0$ and there is no competition, then there will be little reason to delay the launch in order to try and improve the product's performance. If $\pi_0 > \rho_0$ and the competition is low to medium, delaying can be beneficial. Interestingly, this also indicates that an increase in competition can result in an increase in the firm's expected product launch time, contradicting the results of Miltersen and Schwartz (2004).

Observation 4. Enhancing the product's development is useful when the firm can maintain or improve its performance level relative to the market's requirements, for instance when $CC \leq 1$ or $CI \leq q$

Enhancing is an useful option when the additional improvement allows catching up with the competitors, which is the case when competitors are weaker than the firm. Figures 5.10 (c) and 5.11 (c) and factorial tests confirm this. Enhancement, however, is not necessarily used the most frequently when there is no competition, as Figure 5.11 (c) illustrates.

5.8. Empirical Exploration of Use of Delay Option

To demonstrate how these findings might be manifested in practice, we also conduct an empirical exploration. Although, empirical studies have explored the effects of competition on R&D intensity and investment (Lunn and Martin 1986), we are not aware of any empirical studies that explore the influence of competition on firms' decisions to delay, enhance, or abandon the introduction of their products. We investigate 9 product lines, which we characterize as shared markets, from 45 R&D firms, as listed in Table 5.4. We focus on whether the firms' choose to delay the launch of their newly developed product, and the impact of competition.

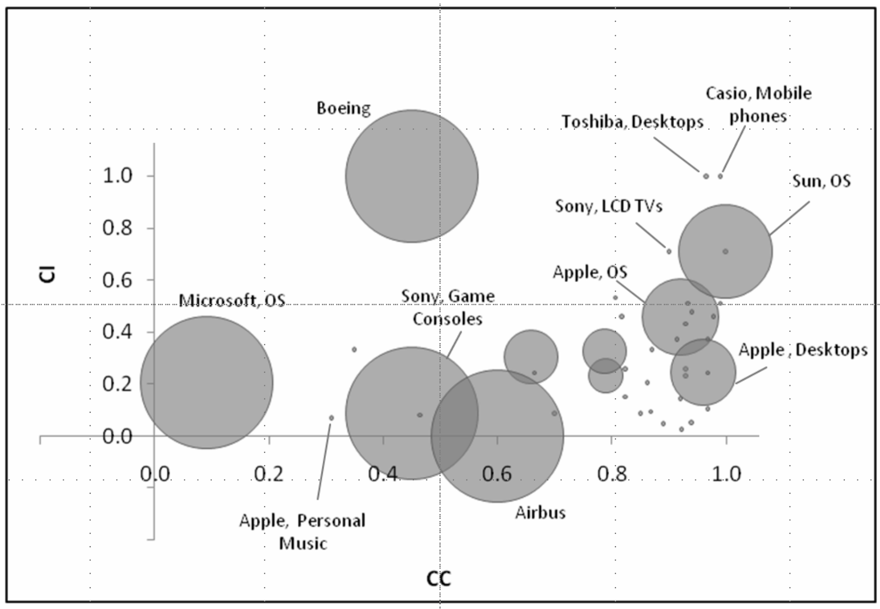


Figure 5.12 **Expected delaying probabilities of the grouped companies**

The Herfindahl and the concentration indices (Hirschman 1964) have often been used as empirical measures of competition. However, they both rely on precise definitions of geographic and product markets (Aghion et al. 2005), the assumption that firms are homogeneous (Boone 2008), and they apply to the product market as a whole, not characterizing a single firm's perspective. Also, in the case where the firm operates in multiple product markets, these indices make it difficult to focus on a single product line. We suggest alternative empirical measures of competition, overcoming some of the shortcomings above.

We use Thomson Gale's 2007 Market Share Reporter (Lazich 2007) and the Capital IQ database as the primary data sources for measuring the competitors' capability, the competition intensity and the frequency of delaying product launch. The competitors' capability, as experienced by a specific firm operating in a certain product line, is measured by $(1 - M)$, where M represents the market share of the firm. We proxy the competition intensity as N_c/N, where N_c is the total number of new products launched by the competitors and N is those launched by the firm during a 5 year period (2003-2007). Product launch announcements were obtained from product related announcements listed in the Capital IQ database, using keywords such as "launch", "available", and "introduction" and were screened for future planned, or speculated, product launch announcements. Records describing upgrades to previously launched products, or regionally customized product launches were removed. Company websites and publicly available press releases were used to confirm new product launches.

The frequency of delaying product launch is determined by the average number of delay announcements made by the firm, per launched product, during a 5 year period (2003-2007), obtained from product related announcements listed in the Capital IQ database. The lists of delay announcements were generated using "delay", "postpone" and "reschedule" keywords (Hendricks and Singhal 1997, 2008). These lists were screened for follow-up announcements, i.e., previously announced delays, which were removed from the list.

Figure 5.12 maps the analyzed firms as a function of CC and CI. The size of the bubbles in the figure indicates the frequency in which a delaying option is used. The figure illustrates that both dimensions of competition influence the firms' delaying decisions, as no single dimension pattern emerges. Note, however, that data presented in this figure includes multiple product lines and in order to conduct a complete statistical analysis to determine the strength of this relationship, we would need to examine each product line separately. Figure 5.12 shows that the same firm might behave differently in different product markets. Sony, for example, uses the delay option very differently in the LCD TV market vs. the game console market.

5.9. Implications of Competition for Value of Flexibility

The results of this chapter demonstrate that the level of competition faced by the firm, and the market environment in which it operates, can significantly affect the value and the use of flexibility. Specifically, we show that the value of development options can be non-monotonic with respect to a change in the fierceness of competition.

We confirm some intuitive results, e.g., an increase in competition reduces the project value, and abandonment is useful when competition is harsh. We also show that delaying a product launch is a valuable option when competition is weak, as it provides a chance to improve otherwise undesirable products. Interestingly, we also find that, under certain circumstances, an increase in competition may result in a delay of the product launch, contradicting the results of Miltersen and Schwartz (2004). We further demonstrate that development options are neither necessarily used more frequently, nor are they more remarkable in a WTA market, where the best performing product captures the entire market, compared to a shared market, where many products gain market share depending on their relative performance.

We illustrate that options can substitute or complement each other, and that these interactions depend on the level of competition. As a result, an NPD project should be valued with all embedded options jointly or otherwise the value of the project might be under- or over-estimated.

Finally, our project valuation framework and the definitions of two dimensions of competition can be useful when deriving theoretical and practical insights and is flexible enough to be extended, for instance, to include multiple product generations, where cannibalization effects can be investigated. Further research should also investigate different cost structures, correlation and mean reversion in the product performance and required performance (e.g., Hahn and Dyer 2008), technology jumps, R&D investment policies (Grenadier and Weiss 1997), and complicated development option structures and their effects on the value of flexibility.

Chapter 6
Conclusions

6.1. Contributions of Dissertation

The preceding chapters suggest that it is pertinent to adapt a balanced approach in the integration of the following components, (i) market uncertainties, which are represented using scenarios, (ii) managerial flexibilities, associated with real options, (iii) the portfolio of investment opportunities, (iv) and the risk management, because these components are interrelated and may influence the optimal investment strategy and the value of the investment. In this setting, the main methodological contributions of this dissertation for the scenario-based modeling are to (i) accommodate multi-level risk management, over several time periods and of confidence levels, (ii) capture correlated uncertainties, (iii) account for the heterogeneity of investors in terms of their level of risk aversion, existing asset portfolio, and financial characteristics, and (iv) acknowledge the prevailing competitive environment on the markets. Table 6.1 summarizes key methodological contributions of chapters 2 - 5 as well as responses to the managerial questions that are presented in chapter 1.

Multi-level Risk Management

Managing market risks on multiple levels, for example in different time periods and percentiles, can be of interest to the decision makers as it allows them to stay within their risk preferences. This may be needed due to financial regulations, if the firm is close to financial distress, or if the planning horizon is so long that the firm needs to be concerned about maintaining a stable credit rating level, for example. This notwithstanding, there has not been much research into multi-level risk management and its implications. Methodologically, multi-level risk management requires, among others, that scenarios are generated such that the relevant risk percentiles are represented in the relevant time periods and that the additional risk constraints are specified.

Table 6.1 Main contributions

Chapter	Key research questions	Methodological contributions	Essential findings
2	How can a forest owner manage risks of the forest stand portfolio efficiently? What are the implications of applying several risk constraints concurrently?	Introduces a multi level risk management in the forest portfolio optimization.	The reduction of extreme risks is initially efficient, in terms of reducing significant amount of risk with small decrease in the expected terminal wealth, but as more risk is reduced the less efficient it becomes. The introduction of risk constraints at several time periods allows forest owners to curtail risks according to their preferences.
3	What are the main drivers of the risks faced by electricity retailers with different risk preferences under price and demand uncertainties?	Develops a framework for dynamic portfolio analysis that accounts for correlated uncertainties.	Risk-averse electricity retailers are most susceptible to the drivers of forward risk premiums, while competitive electricity retailers to the price related uncertainties.
4	How does climate policy risk influence investment behavior and market structure in the electricity sector?	Extends the analysis of investment decisions to account for heterogeneous firms.	Carbon policy uncertainty leads to more concentrated and less competitive markets.
5	How does competition affect the value of real options and their interactions in new product development?	Includes the competitive environment in investment analysis.	The value of real options may not increase monotonically with increasing competition. The competition affects whether options are complements or substitutes.

In particular, chapters 2 and 3 consider the management of multi-level risks. The results of these chapters demonstrate that extreme risks at intermediate and terminal periods can be significantly reduced without a major reduction in the expected terminal cash position.

Correlated Uncertainties

Multiple correlated uncertainties are present in several application contexts, for example in the operations management of a goods or service provider who faces correlated uncertainties in demand and price. They also appear in the financial sector, where the value of an option can depend on the exchange rate and the interest rate, among others. To-date, problems with multiple correlated uncertainties have been approached mostly using simulations or by modeling only the most important uncertainty via a scenario tree. The former approach, however, does not represent well path-dependent decision problems and the latter approach ignores correlations and additional uncertainties.

This dissertation shows that modeling several uncertainties using a scenario-based approach is computationally tractable in multistage models and that scenario tree generation approaches that have initially been developed for the modeling of correlated uncertainties in financial applications can be adapted to other problem contexts as well. In the case of the electricity retailer, chapter 3 shows that correlation between price and load is important to model as otherwise decisions may be suboptimal and risks in CCFAR term underestimated.

Heterogeneity of Investors

Investors can be heterogenous, due to their different risk aversion attitudes, financial conditions, or existing asset portfolio. The heterogeneity of the investors is relevant to model because it has an influence on the investment decisions. For example, a more risk-averse investor is less likely to pursue a risky investment. The heterogeneity of the investors is relevant also, because it may influence which parameters the investors are most sensitive to, which allows the investors to focus their efforts on the estimation of these parameters. The heterogeneity of the investors can be modeled in scenario-based approaches, among others, via exogenous input parameters.

Chapter 4 considers the heterogeneity of the power plant investors under carbon price uncertainty. The results of chapter 4 suggest that larger financially stronger incumbent players, which are typically less risk averse and have lower capital cost than new, project-financed independent power producers are more likely to make the investment decision under carbon policy uncertainty. Also, chapter 4 shows that existing power plants can have an influence on the new power plant investment decision as the new investment can be used to hedge some of the risks of the existing plants. In particular, nuclear and coal fired power plants complement each other and thus hedge each others carbon price risk and hence they can promote interrelated investment strategies.

Similarly the results of the forest portfolio optimization in chapter 2 suggest that the forest owner's risk aversion influences the harvesting strategies. In particular, the risk-neutral forest owner postpones harvesting decisions to benefit from the forest growth while the risk-averse forest owner harvests most of its forests early and let only the youngest and the fastest growing forests grow as their growth hedges against the risk of lower timber prices.

In the context of an electricity retailer, Chapter 3 considers how the heterogeneity of the retailers influences of which input parameters the investor is the most sensitive. Particularly, chapter 3 demonstrates that competitive risk-neutral electricity retailers are more susceptible to price-related than load-related uncertainties. This implies that the risk-neutral retailers should focus their forecasting accuracy on the price-related parameters.

On the other hand, risk-averse retailers are more sensitive to the forward risk premium and load-related uncertainties for which their parameter estimation should focus on.

Investigation of Policy Level Questions

While investors are making their investment decisions independently, their investment decisions can be influenced by the policies. Therefore, it is essential to analyze the impacts of the policies and how these may differ depending on the heterogeneity of the investors. Also, the analysis of the policy implications is useful to obtain understanding how the industry structure is likely to evolve. For the analysis of the policy level questions, the scenario-based modeling approach seems promising.

For example, chapter 4 analyzes the effects of the carbon policy uncertainty for the power plant investment decision-making. The results of chapter 4 show that the carbon policy uncertainties may foster the development of more concentrated and less competitive markets as the new investments are more likely to be made by larger financially stronger incumbent firms than small, project-financed independent power producers. Furthermore, the scenario-based modeling approach is suitable for evaluating the influence of different market intervention mechanisms. Chapter 4 analyzes the influence of setting floors on carbon prices, which based on the results can mitigate the market concentration by particularly encouraging the investments of independent power producers.

Although chapters 2, 3, and 5 do not seek to answer policy questions, they could be extended into this direction. For example, the decision model in chapter 5 could be expanded to analyze how different policies influencing the product development capabilities of the firm and its competitors, such as technology development subsidies, would affect the frequency of launching new products on the market, the quality of the launched products, and the plausible evolution of industry structure.

Impact of Competitive Environment

The competitive environment can have a major influence on the investment decision, particularly in research and development. It is therefore relevant in investment decision analysis. In the scenario-based modeling some characteristics of the competitive environment can be included as an additional uncertainty in the market's requirements. This uncertainty in the market's requirements represents thus all competitors at the aggregate level.

Applying this approach, chapter 5 shows that the level of competition does influence the value of real options and their use in the new product development. The results show that the value of real options can be non-monotonic with respect to increased competition, and that enhancing product development and delaying product launch options are typically most useful when the level of competition is weak.

Furthermore, chapter 5 shows that option interactions, in other words whether options are used to replace each other (substitutes) or exercised together (complements), depend on the level of competition. In practice, this means that if options are substitutes, then the firm may be able to save resources by planning, preparing, and investing in only a subset of the substituting options while all complementary options should be exploited.

6.2. Opportunities for Future Research

These decision models can be extended to examine other kinds of investment problems. The decision model of chapter 2, for example could be re-formulated to value an investment in portfolio of mines (e.g., Kamrad and Ernst 2001) when the excavation amounts are adjustable and the future prices of the excavated raw materials are uncertain. Likewise, chapter 3 could be extended to manage risks of an electricity generator that owns a hydro power plant (e.g., Mo et al. 2001). Here, risks would stem from the uncertainties of water inflows and electricity spot prices.

Further research is still needed to extend the frameworks of chapters 2 and 3 into a rolling horizon setting, where the optimization model is re-run at each time state using the newest available information. This makes it possible to model the firm's operations beyond the initial planning horizon of a model. Then, it is particularly important to consider different hierarchy levels of the resources or contracts and to model the rolling horizon optimization across them while accounting for risks.

Analysis of the competition effects in the new product development can be extended to settings with multiple product generations. In this context important questions are: (i) How does the ability to develop multiple product generations influence the value of real options and their use? (ii) How does the impact of the competition on the option value differ compared to the single generation setting? Beyond this, game theory can provide further research directions as it makes possible to analyze, among others, how the asymmetric information regarding the success of the product development efforts of the competing firms influences for the product development times as well as for the value of the real options (Murto and Keppo 2002, Gibbons 1992).

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Appendix

Lemma 1. The project value under a development strategy A, $P(\Omega)\mid_A$, is a non-increasing function of CI and CC, where A is the set of all development decisions made in all scenarios and time periods.

Proof. Under the development strategy A, an increase in either CI or CC results in a non-increase in the expected difference between performance and market's required performance $E[\pi_t - \rho_t]$, $t > 0$ when $CI \neq 0$ and $CC \neq 0$. As the revenue scaling function $f(\pi_t, \rho_t)$ is a non-decreasing function in $\pi_t - \rho_t$, a non-increase in $E[\pi_t - \rho_t]$ results in a non-increase in the total net revenue $\sigma_t(\mathbf{s^t}, a_t)$. Thus, the project value with an increase in CI or CC under the development strategy A is $P'(\Omega)\mid_A \leq P(\Omega)\mid_A$ confirming that $P(\Omega)\mid_A$ is a non-increasing function of CI and CC.$\square$

Proof of Proposition 1.

Consider two development strategies A and B and assume that the development strategy A is optimal at the current level of the competition, i.e., $P(\Omega)\mid_A \geq P(\Omega)\mid_B$. Assume that when CI or CC is increased, the strategy B becomes optimal, i.e., $P'(\Omega)\mid_B \geq P'(\Omega)\mid_A$ and according to Lemma 1 we have $P'(\Omega)\mid_B \leq P(\Omega)\mid_B$. Hence, the project value with an increase in CI or CC is $P'(\Omega)\mid_B \leq P(\Omega)\mid_B \leq P(\Omega)\mid_A$ and hence $P(\Omega)$ is a non-increasing function of CI and CC. This together with the case that the strategy A remains optimal before and after an increase in CI or CC results that $P(\Omega)$ is a non-increasing function of CI and CC. $\square$

Proof of Proposition 2. We assume first that development options $\tau \in \Omega$ and $\varphi \in \Omega$ are substitutes. The value of the project without the options and the options separately is as follows

$$P(\emptyset) + V(\tau) + V(\varphi).$$

As options are substitutes we can apply Definition 2 $V(\tau, \varphi) < V(\tau) + V(\varphi)$ from which follows

$$P(\emptyset) + V(\tau) + V(\varphi) > P(\emptyset) + V(\tau, \varphi).$$

The righthand side of the inequality represents the value of the project with the development options τ and φ. By Definition 1 as $P(\tau, \varphi) = V(\tau, \varphi) + P(\emptyset)$, we have also

$$P(\emptyset) + V(\tau) + V(\varphi) > P(\tau, \varphi).$$

If we assume that development options τ and φ are complements, we can similarly prove that

$$P(\emptyset) + V(\tau) + V(\varphi) < P(\tau, \varphi). \ \Box$$

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