Hydrogen Infrastructure Decisions through a Real Option Lens

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Table of contents

List of Tables

List of Figures

Chapter 1
Introduction

Fossil fuels are reservoirs of high quality energy assembled by natural systems over long stretches of geologic time. Fuels, petroleum, coal and natural gas, have been the foundation of the industrial revolution and continue to be the essential support of modern society (Bentley, 2002). Although they will remain a significant source of energy and materials for decades to come, renewable energy technologies are widely expected to reduce the role of fossil fuels in world energy consumption in the future (Cuce et al., 2016). The transportation sector has proven to be one of the greatest challenges for the transition to the sustainable energy. In the last decade, one third of the total final energy consumption and more than one fifth of greenhouse gas (GHG) emissions in the European Union (EU) have been produced by the fossil fuel-based transport sector (Dominković et al., 2017). The combustion of fossil fuels to power vehicles and engines has major adverse impacts on the local environment and human health. Although some of these problems can, and have been, reduced by existing technologies such as more efficient engines and hybrid electric vehicles, it is the consensus that eventually a sustainable transportation system with radical technology breakthroughs may still be required to completely resolve these problems (Brey et al., 2013).

Hydrogen has long been suggested as an alternative transportation fuel to replace conventional fossil fuels, and can be twice as efficient through a modified combustion engine that leaves water as the principal residual product. As an ideal technical choice, a hydrogen fuel cell is conceptually a rechargeable battery that produces electricity as a direct product of a chemical reaction: it catalyses the oxidation of hydrogen directly to run electric motors. An electric motor is extremely quiet and not subject to high temperatures, corrosion or any of the structural weaknesses found in other engines. However, the overall commercialization of hydrogen fuel cells has not evolved yet due to current hydrogen production, storage, and the technical limitations of fuel cells (Das et al., 2017). The attention to hydrogen and various research projects may be increasing, but the road towards large-scale use of hydrogen is still uncertain (Hekkert et al., 2005). Instead electric and hybrid electric vehicles are likely to dominate advanced propulsion in coming years. They are currently more economical choices for reducing carbon dioxide emissions, primarily due to the low cost and relatively high-energy efficiency.

The transition from fossil fuel based energy consumption towards sustainable energy solutions is a complex societal process (Kemp et al., 2007; Meadowcroft, 2009). Making investment decisions in such a dynamic, complex environment with different sources of risk is challenging. As a typical example, the development of hydrogen infrastructure will probably start with a few fleet projects, followed by regional investments and ultimately conclude by a commercialization phase. Such an investment process may be interpreted as a sequence of options such that every investment phase creates an option for an investment in the next phase. In such a way that the compound option structure offers much more flexibility to dynamically allocate resources depending on how the sequential stages of the investment project develop over time. In this dissertation, the case study setup of the hydrogen infrastructure project is loosely based on the EU HyWays[1] project. The roadmap assumes a number of investment stages: phase I pre-commercial phase, phase II early commercial phase and phase III full-commercialization. The multi-stage investment will be priced as a compound option, interpreted as a chain of call options to invest. Furthermore, I develop three new models by incorporating the additional features in such investment projects.

In this chapter I first introduce the nature and characteristics of infrastructure investments in general and a hydrogen infrastructure in particular. Subsequently, I give an introduction of real options theory as an appropriate approach to the analysis of a hydrogen energy transition in the transport sector and a motivation behind this choice. Section 1.3 provides the outline of the thesis, and last but not least, I end the section with conclusions and future research.

1.1 Infrastructure Investments in General and Hydrogen in particular

Large-scale infrastructure projects are risky as they require huge irreversible investments, have a long planning horizon, and often use non-standard technology. Consequently, such projects often experience cost overruns or benefit shortfalls and unforeseen difficulties, and thus many large infrastructure projects have experienced situations of financial distress. It is no surprise to see that such risky projects are often separated from the parent company to prevent a failing project from spilling over to the rest of the company (Esty, 2004). Such stand-alone entities are often highly leveraged making them even more vulnerable to delays, cost overruns and unplanned events. The above applies strongly to the energy sector, which typically attracts more project financing than any other sector. The intended energy-transition to more sustainable energy usage even increases the relevance of having an appropriate framework for investment analysis.

Hydrogen has emerged as a possible transportation fuel for addressing long-term, sustainable energy supply, security, and environmental problems. The innovation process for any emerging technology like hydrogen fuel cell technology is usually characterized as complex, with high R&D costs and encompassing high degrees of uncertainties regarding the future of the technology and the diffusion into

[1] HyWays is a research project conducted by the European Commission with the aim of developing a validated and well-accepted roadmap for the introduction of hydrogen in the energy system in Europe. More details can be found at www.hyways.de.

markets. Predicting the development of hydrogen-cell technology is also rather difficult because historical data are unavailable for large-scale commercialization of any new clean energy.

Hydrogen fuel cells have great potential in the long run, but they are currently surrounded by many uncertainties, making planning difficult and fixed plans not optimal. For instance, any effective decision-making often cannot be made completely and accurately at the initial stage because the knowledge about future conditions is unavailable or inadequate. Obviously, there are a number of obstacles that need to be overcome if hydrogen vehicles are ever to penetrate transportation markets, not the least of which is the development of efficient and affordable fuel production and a distribution infrastructure.

The widespread use of hydrogen technology would require significant changes in society's energy infrastructure requiring an upgrade of the existing transport infrastructure to facilitate the adoption of hydrogen fuel cell vehicles. In particular, this implies the need for alternative, hydrogen-based, refuelling stations. A future hydrogen transition relies on strategic planning and necessary investments; energy, economic and environmental analyses must be undertaken in concert with research in improved production, storage, and distribution technologies. The issue of the distribution of a sufficient infrastructure of hydrogen fuelling stations to enable meeting of the initial demand and to satisfy the different roll-out scenarios has been addressed by different authors, in different geographies, and with different methods and approaches. In the literature, there are many approaches allowing for interdependencies between agents through network effects and the analysis of spatial diffusion. Often this approach combines elements like multi-agent (Schwoon, 2006), complex system (Struben and Sterman, 2007) and game theory (Smit, 2003). Details will be discussed in Chapter 5.

To assist the transition, an adequate valuation approach is vital. Indeed, commercializing a new technology requires a revolutionary change in market and technological aspects; one might not anticipate the best path forward from the very beginning. No amount of planning and research can be fully trusted to reveal all contingencies and contingent probabilities from the start. If one wants to analyse hydrogen infrastructure investment decisions, one needs a framework that allows for flexibility and the incorporation of different sources of uncertainty. Our goal is to develop real option models to capture the uncertainties in hydrogen infrastructure development in the Netherlands and further determine its optimal investment strategy.

It is generally believed that the transition to hydrogen-powered transportation faces challenges and uncertainties from market, technical and policy aspects. Market barriers include building a supporting fuel infrastructure, creating a market for new and unfamiliar vehicles, and achieving economies of scale in vehicle production while providing an attractive selection of vehicle models for car-buyers. Whether potential customers will accept the products or whether public users such as transportation companies are willing to procure hydrogen vehicles, still remains unknown. The upfront construction costs will be high and could persist for a decade or more, delaying profitability until an adequate number of vehicles can be produced and moved into consumer markets.

In addition, technical uncertainty should be taken into account in evaluating such innovative projects. It relates to uncertainty of the technology, how it will develop, and of crucial technological barriers and possible to solutions. For instance, for a success commercialization of fuel cell vehicles, they must provide equal performance to a regular internal combustion engine (ICE) vehicle, and perform better in terms of harmful emissions. They will only have a chance to be successful if they are not perceived to be a risk and are able to fulfil the customer's expectations (Schulte et al., 2004). Moreover, fuel cell vehicles will have to compete with alternatives like electrical cars, who have their own technological uncertainties and whose future efficiency is unknown as well.

Finally, policy uncertainty is a crucial factor. Regulation, standards and taxation may affect the development and utilization of the product and may either hinder or support producers and consumers in the adoption process. The position and attitude of public decision makers and the predictability and consistency of policy measures like subsidies, tax-breaks, regulatory requirements as well as the public procurement of vehicles and energy services are crucial to the deployment of hydrogen fuel cell technology into society. High uncertainty in this area may significantly reduce the success of such a profound market transformation.

In this thesis, I apply real options theory to model uncertainties perceived by potential investors connected to the transition process towards a hydrogen infrastructure. I will develop a collection of dynamic approaches to model multiple sources of uncertainties and outline strategies for coping with uncertainties and their resolutions. My aim is to guide investors to make a series of optimal decisions. Throughout this thesis, I measure different sources of uncertainties and develop various real option models to investigate the optimal investment strategy of hydrogen infrastructure development in the Netherlands. In the analysis, I will make extensive use of the phased roadmap HyWays, laid out for the development of hydrogen stations in 10 European countries (Finland, France, Germany, Greece, Italy, the Netherlands, Norway, Poland, Spain, and the United Kingdom) (HyWays, 2008). Our case study is designed by scaling back the European HyWays projections to the Dutch market, based on its population and kilometres of roads.

1.2 Real Options in General

The evaluation of large-scale infrastructure investments is often challenging as it is characterized by irreversible development expenses made under conditions of uncertainty (Trigeorgis, 1996; Lee and Shih, 2010). Real option analysis is an emerging capital budgeting tool, which project managers can use for the allocation of their resources in the face of uncertainty. Two crucial aspects in valuation are the estimation of an expected growth of future cash flows and the estimation of the capital cost. Both aspects significantly influence value estimates. The real option approach supplements the traditional view by emphasizing that it is not just expected value of future profitability that matters, but that the distribution of potential future cash flows also warrants consideration (O'Brien and Folta, 2009). Since a project's actual cash flows are estimates, investors could be making a wrong decision by using discrete time point valuation.

Thinking in terms of options optimizes the way investors deal with uncertainty. Conventionally, good design minimizes risk, which focuses on increasing reliability and making the best decisions in risky situations. The framework of options thinking, however, recognizes that uncertainty adds value to options. The concept of real options is merely an extension of financial options applied to real projects and business valuation. It applies financial option theory to physical assets, which enables the investors to pay a small amount of premium, in control of profit loss, to explore the potential strategic value of the investment opportunity. Real option theory emphasizes the value of waiting to invest, namely the potential value, in addition to net present value (McDonald and Siegel, 1986). As a result, it minimizes the initial critical cost of an investment project and provides conditions for flexible decision-making in the future (Huchzermeier and Loch, 2001). This is crucial to hydrogen infrastructure investments, as even with a mature project or technology, it is still difficult to predict how a transition will exactly evolve and whether it will be successfully implemented.

With the growing acceptance of real option analysis as a modern approach to investment analysis, a great deal of theoretical work exists on how to model and value investment opportunities having real options. In exploratory research on the practice of corporate finance in US firms, Graham and Harvey (2001) showed that 27% of finance officers taking part in their survey had used the methodology in capital appraisal. Similarly, Block (2007) surveyed Fortune 1,000 companies to see if they had picked up on the use of real options to complement traditional analysis. Out of 279 respondents, 40 were currently using real options (14.3%). Real options analysis is now recognized as an important piece in evaluating many capital budgeting problems. Any project that can be delayed, expanded or abandoned based on future states of nature is best analysed by explicitly accounting for the value of the real options created due to project flexibility. This approach can be particularly useful on the type of projects with long investment horizons that are broadly defined and have imprecisely estimated future profitability.

1.3 Outline of the Thesis

This dissertation will use and expand on real options theory to develop models that will be applied to a real project. I apply real options theory to model uncertainties perceived by the potential investors connected to the transition process towards a hydrogen-based transportation system in the Netherlands. This research focuses on the choice of the real option models, on the explicit modelling of three sources of uncertainty (i.e. market, technical and policy uncertainties) and on determining the optimal timing of hydrogen infrastructure development in the Netherlands.

Large-scale capital investments are often sequential and thus typically require a series of irreversible investments, while significant positive project cash flows are realized only when the whole project is completed. As a typical example, the development of hydrogen infrastructure will probably start with a few fleet projects, followed by regional development projects and ultimately conclude with a large-scale nation-wide commercialization phase. Such an investment process may be interpreted as a sequence of options such that every investment phase creates an option for an investment in the next phase. For that reason, an N-fold compound option model is utilized as the benchmark model that in slightly different forms will be used throughout the thesis, except in chapter 3. For simplicity I do not use the compound model there, as it is not a crucial aspect of the focal analysis of that chapter. Table 1-1 includes a brief summary of the characteristics of the next chapters. In terms of uncertainties and research angles, I make use of Geometric Brownian Motion (GBM) and Jump processes in different combinations to capture the variations embedded in the underlying project value, focusing on different type of uncertainties.

Table 1-1: Summary of the characteristics of the next chapters

Chapter	Modelling framework	Uncertainties	Case	Focus
2	N-fold compound options	1 GBM for market + technological	Hyways, Dutch regional pilot	Relevance of barrier
3	Simple options	GBM for market, jumps for technology vs GBM for market, GBM for technology	Hyways, the Netherlands	Modelling technical uncertainty
4	N-fold compound options	GBM for market Discrete probability for technology Jumps for policy	Hyways, the Netherlands	Relevance of policy uncertainty
5	N-fold compound options	1 GBM for market + technological	Hyways, the Netherlands	Feedback loop from building strategy to adoption

1.3.1 A Barrier Options Approach to Modelling Project Failure

Standard option models assume that the option stays alive irrespective of the value of the underlying asset during the lifetime of the option, which conflicts with the reality of the innovation diffusion process for any emerging technology. For example, governments or regulators may cancel or cut the funding if technological progress stays below their expectations; or investors may abandon their plans when an unplanned event causes a very low expected present value of the underlying investment because they do not want to spend additional money until the moment of the next decision point to proceed (or not) to the next phase. A real-world example of such termination is a pilot project for hydrogen-fuelled buses in the Amsterdam public transport system. After its start in 2008, it encountered a leakage between the hydrogen tank and the hydrogen refuelling system leading to immediate project termination (Backhaus and Bunzeck, 2010). Failure to account for such knock-out characteristics may lead standard real option models to overvalue a project.

Therefore, in Chapter 2, I contribute to the literature by including a knock-out barrier option in the N-fold compound real option model to take account of immediate project failure – a so-called sudden death – in a multi-stage sequential investment project. In my view, the possibility of sudden failure in large infrastructural investment projects or in the development of innovative technologies should be taken quite seriously. Inappropriately ignoring the possibility of sudden failure can have large and adverse consequences for investment decision-making. The model allows for explicitly incorporating the default possibility of large-scale energy infrastructure projects. I propose to map the unforeseen investment failure through the evolution of firms' underlying value. Once the barrier is hit, it will result in partial or complete failure. The barrier will act as a lower bound for the underlying variation, and a real option model with barrier will therefore be used to account for an investment opportunity with potential premature failure.

I apply this model to a regional case of hydrogen infrastructure investment in the Netherlands and further determine the barrier through a pessimistic scenario. In the case study, I use a number of different external sources to set the parameters in the model. Subsequently, I compute the hydrogen infrastructure project value in the case of a barrier of 50 and 70 percent of the Net Present Value (NPV) of the project cash flow in the full commercialization phase, and benchmark it against valuation through an NPV model and a no-barrier real compound option model. Sensitivity analysis shows that both the position of the barrier and the aggregated volatility has a strong impact on the option value.

Overall, my results indicate that even for the least conservative valuation method, the no-barrier option model, no profitable business case can be made for the development of hydrogen as a sustainable transportation fuel, which is consistent with earlier literature. Note though that all three real option models are much closer to the acceptance threshold – imposed by the first phase investment costs – than the NPV valuation.

Subsequently, I provide some suggestive scenarios where plausible tax schedules can be designed to overcome the starting problems for hydrogen infrastructure development. A 25 percent excise duty discount is sufficient for a positive decision in the no-barrier framework. For the 50 percent barrier, one needs a discount between 25 and 50 percent, and for the 70 percent barrier a tax discount of somewhat over 50 percent is necessary. To the extent that sudden project failure would be predominantly caused by potential reversals in political support, an inexpensive way to make the development of hydrogen infrastructure – and other similar projects – more attractive would be to design credible long-term political commitments to this type of development.

Policymakers are indeed key players in creating incentives for companies to invest in sustainable energy solutions or to accelerate the development process (Blyth et al., 2007). This important element is investigated further in chapter 4, which will focus on the role of policy uncertainty as a separate source of risk, parallel to market and technical uncertainty.

1.3.2 Modelling Technical Uncertainty with Jump Process

The choice of the appropriate stochastic process and its parameters appears crucial for real option valuation. Theoretically, one would want the selected stochastic model to optimally reflect the project's characteristics. In the literature, a range of stochastic processes is used to model technological uncertainty, and different types of technical uncertainty are distinguished. A clear link between the type of uncertainty and the choice of stochastic process appears absent. Although the different approaches share a common goal, they differ markedly in their underlying assumptions and definitions.

In chapter 3, I compose and discuss a broad class of asset pricing models under technical uncertainty, and further evaluate their performance. This chapter contributes to the literature by investigating the robustness of real option valuation under different stochastic processes. In particular, the analysis is limited to jump diffusion models and standard Geometric Brownian Motion (GBM) models. Within the class of jump diffusion models, I further focus on asymmetric – positive or negative – and symmetric jumps. In particular, I investigate whether approximating asymmetric and symmetric jump processes by an augmented GBM leads to significant pricing errors. Both stochastic models are being priced with European options for a wide range of parameters characterizing the jump processes. Note that in the empirical testing, I will again use the HyWay pilot case in such a way that allows me to evaluate relative performance in a consistent way.

Overall, I find that the augmented GBM model under-prices (overprices) the option in the case of positive (negative) jumps. It also overprices in the case of symmetric jumps. The overpricing and under-pricing increases with jump probability, mean jump size, and jump size volatility and decreases with initial project value (out-of-the-money options). My results suggest that using an appropriate augmented GBM model to price real options on projects with complex jump dynamics may not lead to significant valuation errors or incorrect investment decisions. However, failure to correct for the average drift that comes from the jump process, or to appropriately take into account the various sources of volatility – both jump size volatility and expected jump size – when specifying the augmented GBM model, may result in significantly incorrect option prices.

1.3.3 Incorporating Policy Uncertainty in a Compound Option Framework

In chapter 4, I extend the generalized N-fold compound option model developed by Cassimon et al. (2011b) and incorporate policy uncertainty. Following their approach, the expected revenue based on the initial estimation of the potential market size will be modelled by Geometric Brownian Motion (GBM). In addition, discrete success-failure probabilities of the project are used to reflect technical failure at each investment stage. The positions and attitudes of policy makers are crucial to the deployment of hydrogen fuel cell technology into society. Policy uncertainty will be the focus of this chapter with the characteristics being modelled through a Poisson jump process, which is added to the sequential compound option. This model will be used to evaluate the risks associated with uncertainty in climate change policy, namely the stability of policy and the impact of different forms of policy changes. With such a complete view, I make recommendations to investors on how they should perceive policy uncertainty and to policy makers on how policy could be implemented to reduce such risks associated in the investment.

This chapter empirically applies the extended compound option model to the HyWays case of hydrogen refuelling infrastructure investments in the Netherlands. My findings indicate that an investment project that would be feasible when only market and technical risk are considered can become infeasible when policy uncertainty is incorporated. This is not the case when policy uncertainty is symmetric. If policy shocks with a positive and negative impact on the project value are equally likely, the upward potential of future positive policy shocks outweighs the value reduction from negative shocks. In that case, the project actually becomes more attractive. However, if negative shocks are dominant in size or frequency, policy uncertainty may prevent otherwise attractive and desirable investments. Obviously, for investors it is important to correctly assess the characteristics of policy uncertainty. Policy makers need to be aware that uncertainty with respect to negative policy shocks can be an important impediment to large investments in risky new technologies and infrastructure projects. To encourage such investments, it appears important to formulate clear policy goals and instruments as well as designing a clear regulatory and institutional framework. Moreover, a credible commitment to keep policies in place over a long period is crucial, too. In such a setting, where policy uncertainty is reduced to very low levels, market and technical uncertainties will be the main drivers of investment decisions.

1.3.4 Hydrogen-Fuel Infrastructure Investment with Endogenous Demand

The introduction of an alternative transport fuel always bears the challenge of a "chicken and egg" problem. While consumers will only become interested in and start switching to a new fuel if sufficient refuelling stations are available, the industry will only start investing in the development of fuelling infrastructure if the market is sufficiently developed and existing stations are economically viable. Theoretically, on one hand, from the infrastructure builder's cost perspective it is important that there are just enough stations to ensure satisfactory utilization of each station and keep the costs as low as possible. An underutilized station drives up costs significantly. On the other hand, potential adopters will perceive adequate refuelling availability over a sufficiently large refuelling coverage area as a critical factor in their decision to switch to hydrogen fuel cell vehicles. This implies a choice between having higher fixed costs initially by building more stations at a faster pace in combination with higher potential revenues due to higher and faster adoption or investing at a slower speed with lower costs but also slower expected growth of revenues.

In chapter 5, I develop a real option framework that studies this impact of the adoption speed and investment decision, and further analyses the consequences of this dependence for optimal investment. To this purpose, I integrate the N-fold real option model with a Generalized Bass model that computes the speed of adoption as a function of available refuelling stations. This way, I explicitly incorporate the impact that realized investments in new infrastructure may have on adoption speed in a real option's framework for investment decisions. In this application, I develop the diffusion process in such a way that it models future demand as a function of the number of available refuelling stations. As an illustration, I apply the combined model to the case of the nation-wide introduction of infrastructure investments for hydrogen-fuelled cars in the Netherlands. I perform a scenario analysis where six different infrastructure investment strategies are combined with four different parameterizations of the model. The variation in parameterization captures different degrees of demand sensitivity to existing infrastructure.

This exploratory research will shed light on the way the optimal investment path depends on the sensitivity of demand to available infrastructure and the consequent process of market penetration, and provide direction for investors and policymakers. This chapter in particular aims to tackle the issue of interdependency between sufficient refuelling infrastructure and consumer adoption, and its impact on optimal investment decisions. The results show that ignoring the potential interaction between the speed with which the required infrastructure will become available and the adoption process may lead to suboptimal decisions with respect to the optimal timing of investment spending as well as with respect to the assessment of the feasibility of the project in general.

1.4 Limitations and Future Research

This thesis examines hydrogen infrastructure investments and discusses the opportunities and uncertainties surrounding the real implementation. Throughout this thesis, I introduce a range of challenging problems associated with traditional valuation in sustainable energy investment projects; but in this chapter, I discuss the limitations and propose possible directions for future research.

In general, limitations of empirical research are mainly related to the data and the methodology employed. Specifically the lack of actual data is a general limitation in this study. More data could help to improve the accuracy of model parameter calibration and thus the robustness of the results. My case study is also developed based on the roadmap assuming three investment phases: phase I is the pre-commercial phase, phase II is the early commercialization phase and finally, phase III is the full commercialization phase. I also apply data from secondary sources based on a few references. In this study, I use mainly data available from the HyWays research project, as I believe these data are the best source available. Indeed, these data can influence the conclusion I draw in the coming chapters. However, this case study is only used as an illustration for the models, the aim of the thesis has never been a detailed cost-benefit study with the latest numbers on the profitability of actual project. The numerical estimations from the model should rather be interpreted as a strategic exploration of firms' investment decisions rather than an accurate prediction. Moreover, a generic issue among all the chapters is that some important uncertainties are being modelled independently. I apply different approaches on market, technical and policy uncertainty and each as the focus of each individual chapter. A direct extension of this research is to include the correlation among different sources of uncertainties.

In Chapter 2, I contribute to the literature by including a knock-out barrier option in an N-fold compound real option model to take account of immediate project failure in a multi-stage sequential investment project. A direct extension of this study is to include additional research on determining the barrier. Additionally, it might be interesting to introduce a dynamic set-up in the estimations to bring in real life heuristics in real option modelling. What kind of barriers do investors in real life have in mind? What is the minimum level that is acceptable?

It will also be interesting to further explore the determination of the barrier. Future research could go deeper in the sense that volatility is the main factor in uncertainty measuring. Technology projects are often specific assets for the firms that invest in them, which are not subject to the valuation of the market. This violates the assumption of market tradability on which the asset option pricing theory is based. It can be very challenging to estimate the volatility parameter for a real option model with no historical returns for assets that are perfectly correlated with the project cash flows. In some cases, where the project involves production and sale of a commodity, the historical commodity prices can be used, but even in this case the correlation is only partial.

In Chapter 3, I contribute to the literature by investigating the robustness of real option valuation under different stochastic processes. Given the scope of this study, my analysis is limited only to jump diffusion models and standard Geometric Brownian Motion models. There are different branches of literature on technical uncertainty, and within each branch a wide range of modelling approaches have been used. For future research, it would be interesting to increase the scope of comparison and investigation on the sensitivity of various modelling choices.

In Chapter 4, I focus on the role of policy uncertainty as a separate source of risk, parallel to market and technical uncertainty. It would be interesting to estimate policy uncertainty in general and for the energy transition in particular from real data and evaluate whether symmetric or asymmetric shocks are more common. In this way, one could include policy uncertainty more precisely based on the estimated distribution. In addition, the transition to sustainable energy system is a dynamic process, since in the real world the technology itself evolves. The uncertainties and rules guiding its development co-evolve with policy decisions, user behaviours and business strategies. These relationships should somehow also directly influence the investment decision on hydrogen infrastructure developments.

In Chapter 5, I develop a combined model to study the dependency of market adoption over the hydrogen refuelling infrastructure investments. From an empirical prospective, the direct estimation of a simple Bass model or an extended Geometric Brownian Motion model for the hydrogen case is infeasible due to the lack of actual data on infrastructure investment and consumer adoption. This is similar to many previous disruptive technologies prior to market entry. More research is needed to obtain realistic estimates of the magnitude of the relevant parameters that govern the adoption diffusion process for new technologies. This is also left for future research.

Chapter 2
A Barrier Options Approach to Modelling Project Failure: The Case of Hydrogen Fuel Infrastructure[2]

2.1 Introduction

Over the past decades, real option modelling has become an increasingly popular approach for the valuation of large infrastructural projects, for the valuation of innovative projects in the natural resources and energy sector and in technology-intensive industries. Examples of the former include applications to toll road development (Rose, 1998), airport expansion (Smit, 2003), and highway development (Zhao et al., 2004). Examples that apply real option valuation to natural resources and energy problems include Fisher (2000), Sanders et al. (2013) and Sarkar (2009). Applications of real option modelling of innovative projects in technology-intensive industries can be found in Cassimon et al. (2004, 2011a), Fuss et al. (2008), and Schwartz (2004). Real option valuation is preferable to net present value computations because it takes into account the value of waiting and operational flexibility.

Typically, real option valuation is based on the hypothesis that the underlying project value changes over time according to some stochastic process with high volatility (e.g. Conrad and Kotani, 2005). The only uncertainty taken into account is the possibility of a deviation from an expected condition based on the variation of one or more environmental conditions that drive the stochastic process. Standard option models assume that the option stays alive irrespective of the value of the underlying asset during the lifetime of the option. However, some investment projects may have knock-out features that may immediately and completely terminate the model at one of two decision points. Here, one may think of a physical catastrophe causing the loss of crucial societal and/or governmental support, insurmountable technological problems, or unexpected extra costs requiring additional funding at excessive prices leading to financial distress. Less dramatically, governments or regulators may cancel or cut the funding if technological progress stays below their expectations; or investors may abandon their plans when an unplanned event causes a very low expected present value of the underlying investment as they do not want to spend additional money up until the next decision point to proceed or not to the next phase. A real-world example of such termination is a pilot project for hydrogen-fuelled buses in the Amsterdam public transport system. After its start in 2008, it encountered a leakage between the hydrogen tank and the hydrogen refuelling system leading to immediate project termination (Backhaus and Bunzeck, 2010). Failure to account for such knock-out characteristics may lead standard real option models to

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[2] A modified version of this chapter has been published as: Engelen, P. J., Kool, C., and Li, Y. (2016). “A barrier options approach to modelling project failure: The case of hydrogen fuel infrastructure”, Resource and Energy Economics, 43, 33-56.

overvalue a project.

In this article, I extend the existing real option literature by including a (down-and-out) barrier into an N-fold compound real option framework to value a large and innovative infrastructure project. An N-fold compound option framework typically captures the decision moments of a multi-stage investment project where the different phases can be seen as a sequence of real options and where each phase gives the option to move to next phase (Cassimon et al., 2004). I develop and present a model to estimate the fair value of an innovation project that will be knocked out if at any time the underlying project value breaches the minimum level that is acceptable to investors. I thus model an exogenously defined minimum constraint that the investor of the project is not willing to fall short of.

Options with barrier features are quite common in the financial option literature. The original pricing formula for continuously monitored knock-out barrier options goes back to Merton (1973). Recently, financial options with barriers have been frequently used to analyse a firm’s default probabilities (see Broadie et al., 1997; Brockman and Turtle, 2003; and Kou, 2003). The basic idea is that corporate equity cannot be modelled as a standard path-independent call option on the value of the firm. It will always be in the interest of the equity holder – that is, the holder of the option on the firm’s residual value – to hold on to the option until expiration. However, before expiration the bondholders may pull the plug and declare bankruptcy if firm assets drop to a critically low value. Consequently, it is argued that equity should be modelled as a path-dependent option that can be terminated prior to expiration. A similar reasoning applies to the real option approach of valuing large and innovative infrastructure projects. Cost overruns, financial distress, extra funding needs, or the breakthrough of a competing technology can lead to an immediate termination of the project prior to expiration of the option and the next decision moment. This is particularly important for project financing. To the best of our knowledge, this is the first paper to apply barrier options in an N-fold compound real option setting.

I will apply our barrier approach to the case of hydrogen infrastructure development. In our view, the hydrogen case is not only an appropriate application of a barrier model but it is also of relevance in its own right. From a societal perspective, the search for a feasible and sustainable source of energy to reduce the emission of greenhouse gasses has increasingly gained priority, and hydrogen is one of the most attractive alternatives known so far (Adamson and Pearson, 2000). I focus on the development of a hydrogen fuel station network for cars. For a successful transition to hydrogen-powered transportation one needs to solve crucial technology difficulties, create a market for the new vehicles, and further achieve economies of scale in vehicle production. An innovation such as hydrogen fuel cell technology will only have a chance to be successful if it is perceived to be safe, can reach equal performance as a regular internal-combustion-engine vehicle, and have the supporting infrastructure for refuelling (Schulte et al., 2004). The latter requires significant amounts of irreversible investments over a decade or more until large-scale commercialization can be reached (Schoots et al., 2010). In short, investing in a new hydrogen infrastructure will face huge market risks as well as technological risks and a substantial probability of intermediate failure and abandonment.

So far, energy analysis in general and hydrogen analysis in particular mostly uses sensitivity analyses, scenario studies or simulations to assess the impact of specific uncertainties. Many hydrogen infrastructure development reports adopt scenario-based simulations, for instance, HyWays, the U.S. Department of Energy Roadmap[3] and HITA[4]. Moreover, a number of studies (Agnolucci, 2007; Chang et al., 2007; Joffe et al., 2004) have analysed and compared the performance of different hydrogen pathways. Thomas et al. (1998) evaluated different market penetration scenarios to estimate the likely number of fuel cell vehicles that might be sold in the United States over the next few decades. Ogden (1999a) developed an infrastructure case study for hydrogen-fuelled vehicles in Southern California. Mulder et al. (2007) made use of a top-down penetration scenario to assess different technology configurations in terms of chain efficiency and CO2 emissions. Similar research was conducted by Wietschel et al. (2006) to evaluate hydrogen technologies under different costs, emissions and efficiency scenarios.

Clearly, it is preferable to use a more accurate capital budgeting decision-making framework such as real option modelling (Abadie and Chamorro, 2008). It can directly transform uncertainties into flexibilities and provide more insight in the dynamics of the project (Guerrero, 2007). Real options are now widely accepted in the literature to value and select projects with strategic issues and operational flexibilities (Dixit and Pindyck, 1994; Trigeorgis, 2000). To our knowledge, Benthem et al. (2006) is the only real option application on hydrogen.

The paper extends the existing literature in two ways. First, this is the first article to incorporate a barrier option in an N-fold compound real option setting. Second, we show how this can be applied to the relevant real-world case of the development of new infrastructure for hydrogen vehicles. Our analysis shows that even for the least conservative valuation method, no profitable business case can be made for the development of hydrogen as a sustainable transportation mode. However, I do provide some suggestive scenarios that show that plausible tax schedules can be designed to overcome the starting

[3] See also http://hydrogendoedev.nrel.gov/roadmaps_vision.html.

[4] *Hydrogen Infrastructure Transition Analysis* by the U.S. National Renewable Energy Laboratory (NREL). See for more information: www.nrel.gov.

problems for hydrogen infrastructure development. To the extent that sudden project failure would be predominantly caused by potential reversals in political support, a cheap way to make the development of hydrogen infrastructure – and other similar projects – more attractive would be to design credible long-term political commitments to this type of development.

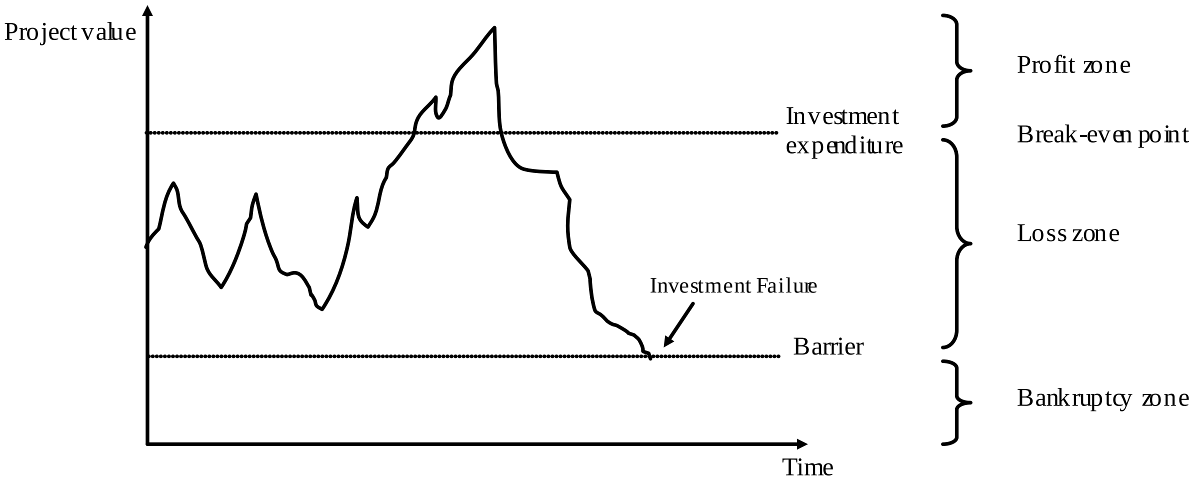
The rest of the article is organized as follows. Section 2 introduces the concept of investment failure and its relation to barrier options. In Section 3, I present the basic model and discuss its main features. Next, Section 4 introduces the case of hydrogen infrastructure investment and presents the case results when applying the model. In section 5, I test our results with real-world business expectations. Finally, section 6 summarizes and concludes.

2.2 The possibility of default in large-scale infrastructure projects

Large-scale infrastructure projects are risky as they require huge irreversible investments, have a long planning horizon, and often use a non-standard technology. Consequently, such projects often experience cost overruns or benefit shortfalls and unforeseen difficulties. For a sample of 258 transportation infrastructure projects, Flyvberg (2007b) showed that the frequency of cost escalation for a randomly selected project was 86%, with an average cost escalation of about 28%. The size of the standard deviations of the cost escalation (between 30 and 60%) illustrates further the huge uncertainty with respect to cost overruns. Revenue overestimation occurs frequently as well. For instance, Flyvbjerg, Skamris Holm and Buhl (2005) found that rail passenger forecasts are overestimated by an average of 105%. Examples of projects hit by cost overruns and benefit shortfalls abound: Boston’s Big Dig, the Channel tunnel, the Quebec Olympic stadium, Toronto's Sky Dome, the Sydney Opera House, London’s Millennium Dome, Hannover’s Expo 2000, Athens’ 2004 Olympics, the Copenhagen metro, the Oresund Bridge between Sweden and Denmark, and the Great Belt rail tunnel linking Scandinavia with continental Europe (Flyvbjerg, 2007a). Moreover, since it is quite difficult to specify ex ante the relevant risks of large-scale projects, such projects are vulnerable to unforeseen events (Szyliowicz and Goetz, 1995).

For the above reasons, many large infrastructure projects have experienced situations of financial distress. Examples include large-scale projects such as Eurotunnel, Iridium, Globalstar, Bangkok’s Skytrain or Canary Wharf (Esty, 2004). A detailed case study on the financial distress of the Eurotunnel project can be found in Vilanova (2006). Miller and Lessard (2000) showed that about 40% of large-scale engineering projects between 1980 and 2000 performed poorly, leading to total abandonment or restructuring after financial distress. It is no surprise to see that such risky projects are often separated from the parent company to prevent a failing project from spilling over to the rest of the company (Esty, 2004). Such stand-alone entities are often highly leveraged making them even more vulnerable to delays, cost overruns and unplanned events. Obviously, knowledge of the project default level is crucial in determining the economic viability of the infrastructure project. As the energy sector attracts more project financing than any other sector, our model and case study on energy innovations are very relevant for both companies as well as policy makers.

Figure 2-1: The decision-making diagram of a barrier real option



In the literature on default risk, structural models postulate that default occurs when the value of a firm's assets drops below the debt value. For instance, Duffee (1999) used a contingent claims valuation to support this assertion and to find the probability of default. In a similar way, large infrastructure projects might also go bankrupt if the economic value of the project drops below a certain threshold value. Figure 2-1 illustrates this process by depicting a possible path of the project value over time. When the project value increases over and above the investment expenditure, the option to invest in the project is "in-the-money" and calls for (early) exercising the investment option. I label this the profit zone in Figure 2-1. When the project value stays below the investment expenditure, the option to invest is "out-of-the-money". In this case investing in the project is a loss-maker, but the company holds on to its option as the project might become profitable in the future (loss zone).

When the project value drops below a certain threshold value or barrier, default occurs and the entire project is abandoned, the bankruptcy zone in Figure 2-1. Default may be due to market reasons, for instance, when the project cannot service its interest and debt payments anymore or when the project cannot find additional financial resources to cover its cost overruns. At the moment of financial distress of the Eurotunnel project in 1995, its project value amounted to £ 3,59 million, while its outstanding debt was equal to £ 6,35 million (Schueler, 2007). Other reasons for hitting the barrier include technological failure, breakthrough of a competing technology or political interference.

Real option valuation of a project that is characterized by a knock-out feature can be done with a down-and-out barrier option. The project, and the option, is immediately terminated if the underlying asset value reaches a specified barrier level prior to the expiration date of the option. For our basic model, I use an N-fold compound option framework as it captures the decision moments of a multi-stage investment project. This matches well with the various transitional phases of the development of a hydrogen-based transportation system. I model market and technological uncertainty as a two-dimensional Brownian motion with both market and technological uncertainties rolling together for an increased volatility (see next section). In addition, I impose a barrier that will work as a restriction to the stochastic process and may cause it to stop earlier.

Our modelling approach allows for a knock-out feature that terminates the entire project. Similar types of problems have been analysed in the literature. To cope with the possibility of permanent project failure, Schwartz and Moon (2000) developed a real option model that incorporated a Poisson process to evaluate R&D projects with a chance of a catastrophic event that causes the project's value to jump to zero. They solved the ensuing valuation problem by numerical approximation. Cassimon et al. (2011b) used discrete success-failure probabilities at each stage of a pharmaceutical project to reflect technical catastrophic failure in a compound option framework. While Poisson jumps and discrete-time failure rates have their merits, both approaches assume the project value drops to zero.

Although this is an important feature relevant to many high-risk projects, not all events are of a catastrophic nature causing the project value to jump to zero. Our barrier model allows for less dramatic events to terminate the project, without the need for the project value to drop completely to zero. This characteristic is especially valuable in a context of project financing, such as our case study on the establishment of a hydrogen infrastructure network. In many cases private investors pull out of a project without the occurrence of a catastrophic event. Cost overruns, changes in consumer preferences, changes in government support, developments of competing technologies or changes in societal perceptions of certain technological solutions may cause private investors to decide to pull their money out of the project even though the project value did not drop to zero. Such investment behaviour occurs as the project value drops below a minimum threshold necessary for its financial viability. In high-risk environments, private investors indeed demand high expected returns. Events that cause the project value to become financially unattractive for private investors because the expected return would remain below their target value may trigger a knock-out feature. Poisson jumps and discrete-time failure rates do not allow for such less drastic events.

From a private investor's point of view this is a valuable extension of the existing knock-out modelling approaches. That is not to say that catastrophic risks that force project values to drop to zero are not important for hydrogen projects. In fact they still are and are still captured by our approach. I only argue that the barrier model allows handling of a wider range of possible knock-out features. In project financing the barrier is therefore the minimum project value acceptable to private investors.

I will first develop the N-fold compound barrier option model in section 3 and then apply it to the hydrogen infrastructure case in section 4.

2.3 The Model

2.3.1 Theoretical framework

As the aim of the chapter is to analyse the viability of a hydrogen infrastructure project from a private investor's perspective, I use a Geometric Brownian Motion for the underlying stochastic process. Our choice is dictated by having a tractable analytical solution in a closed-form format that is easier to understand by decision-makers in the business setting of our case study. A closed-form expression for barrier options under the Geometric Brownian Motion hypothesis is well known. Incorporating the barrier feature into the closed-form N-fold compound option solution of Cassimon et al. (2004), I prefer to keep a closed-form expression for our model as well. Moreover, because our focus is on the incorporation of the barrier component, I will keep the remainder of the framework as standard as possible.

Obviously, one can find alternative specifications for the underlying stochastic process in the literature, such as mean-reverting or Poisson jump specifications. Closed-form expressions for other stochastic processes, however, are very few. Since a jump-diffusion model extends the classical diffusion modelling framework by adding jumps to capture large and sudden changes in the underlying state variable, such specification could be an alternative for our choice, too. However, because of the difficulty in obtaining general analytical expressions for barrier options under the jump-diffusion framework, much of the previous work has focused on complex numerical approximations or Monte Carlo valuation methods.

Specifications that use mean reversion, such as an Ornstein-Uhlenbeck process or a square root model, are frequently used to model interest rate dynamics (Ritchken, 1996). It is often assumed that the asset price might behave randomly in the short term, but tends to converge to an equilibrium level in the long run (Cox, Ingersoll, Ross, 1985). Again, analytical solutions and tractability is often a problem. Mean reversion is also less suited to describe the asset price behaviour in our case study.

This leads to our assumption that the evolution of the underlying project value can be written as a Brownian motion $\{V_t\}_{t\in[0,T]}$. The uncertainty is defined in a filtered probability space $(\Omega, \mathrm{F}, \mathrm{P})$, where Ω includes all possible instants of the stochastic variation of V_t. Given the information filtration F, the market value of a claim on the expected future cash flows is represented by V_t under physical probability measure P at time t. I assume the market to be complete with no transactions costs. The risky investment project dV_t will follow the stochastic process:

$$dV_t = \mu V_t dt + \sigma_M V_t dW_t^M + \sigma_T V_t dW_t^T. \qquad [2\text{-}1]$$

With μ the expected rate of return on the project, σ_M the market uncertainty, σ_T the technological uncertainty, dW_t^M and dW_t^T are stochastic variables that follow a Wiener Process in which $dW_t^j \sim N(0, \sqrt{dt})$ for $j = M, T$.

The complexity of the model can be reduced by collapsing market uncertainty and technological uncertainty into one factor with volatility $\tilde{\sigma}$.[5] Formally, the combined volatility is defined as $\tilde{\sigma} = \sqrt{\sigma_M^2 + 2\rho\sigma_M\sigma_T + \sigma_T^2}$. Total volatility depends on the degree of market and technological uncertainty and on the correlation ρ between these two sources of stochastic shocks. $\tilde{\sigma}$ is higher when market uncertainty σ_M and technological uncertainty σ_T are positively correlated, for instance when market acceptance (demand) goes up as technological advances occur. It is lower when they are negatively correlated. In the simplified model, dV_t will follow a simple Geometric Brownian Motion:

$$dV_t = \mu V_t dt + \tilde{\sigma} V_t dW_t^{MT}. \qquad [2\text{-}2]$$

2.3.2 *Option valuation*

I first present the option valuation model for a simple real barrier option before incorporating the barrier into an N-fold compound real option framework.

[5] Cortazar et al. (2001) used a similar approach to evaluate natural resource exploration investments with price and geological-technical uncertainty, but without a barrier as a restriction to the stochastic process.

2.3.2.1 European barrier option

The value of barrier options is calculated path dependently with trigger prices. Assume a call option with maturity time T and strike price I has zero value if the underlying project value V_t falls below the barrier B at some point before maturity. Then the option value at any time t can be written as:

$$C(t,V) = e^{-r(T-t)}E^{Q}[(V_T - I)^{+}1_{\{max_{0\le t\le T}V_t \ge B\}}]. \qquad \textit{[2-3]}$$

Here, E^Q denotes the expectation under the risk neutral measure Q. $(V_T - I)^+$ is short-hand for $\max[(V_T - I), 0]$, and $1_{\{\max_{0\le t\le T} V_t \ge B\}}$ is an indicator function that takes the value 1 when the underlying project value V does not fall below the barrier B during the lifetime of the option and the value 0 when it does. The barrier B is the minimum level of the underlying project value that is acceptable to investors.

I assume that $C \in [(0,T) \times (B,\infty)]$, that C is continuously differentiable in the first variable, twice continuously differentiable in the second variable and satisfies the partial differential equation

$$\frac{\partial C(t,V)}{\partial t} = rC(t,V) - rV\frac{\partial C(t,V)}{\partial V} - \frac{1}{2}\tilde{\sigma}^2 V^2 \frac{\partial^2 C(t,V)}{\partial V^2}. \qquad \textit{[2-4]}$$

Here the option price is computed based on the expected option payoff under the equivalent martingale risk neutral measurement, discounted at the risk free interest rate r.[6]

I define $\beta = \frac{B}{V_0} < 1$, where the parameter β reflects the size of the barrier relative to the initial underlying project value. Extra boundary conditions are determined by the nature of the barrier. Failure occurs at the first time t, where $t \in [0,T]$, at which the project value V_t fails to reach the level B. If so, I assume the option expires without value[7]:

$$C(t,B) = 0, 0 \le t < T. \qquad \textit{[2-5]}$$

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[6] One of the alternative approaches is to define this expected rate of return as the risk-adjusted discount rate for the asset's cash flow. With the capital asset pricing model, expected return on an asset is considered as a function of the risk-free rate and the risk premium. Instead of assuming that the project's value grows at an uncertain expected rate, we assume that it grows at the risk-free rate. This should not be viewed as particularly restrictive. We refer to Dixit and Pindyck (1994) for further details.

[7] There might also be situations where the project will have some scrap value upon default. In that case the model incorporates a non-zero payoff R.

In case the project value remains above the barrier B during the whole lifetime of the option, the end value of C is equal to:

$$C(T,V) = (V_T - I)^+, B \leq V_t , \beta \leq 1. \qquad [2\text{-}6]$$

The probability of an investment failure is defined as the chance at time t that the underlying project value falls below the barrier before option maturity T. Based on Brockman and Turtle (2003), this probability can be written as:

$$P_t(V_T \leq B) = \Phi\left(\frac{ln(\beta) - \left(r - \frac{1}{2}\tilde{\sigma}^2\right)(T-t)}{\tilde{\sigma}\sqrt{T-t}}\right) + \beta^{\frac{2r}{\tilde{\sigma}^2}-1}\Phi\left(\frac{ln(\beta) + \left(r - \frac{1}{2}\tilde{\sigma}^2\right)(T-t)}{\tilde{\sigma}\sqrt{T-t}}\right). \qquad [2\text{-}7]$$

Note that the probability in Equation [2-7] is increasing in the horizon considered, since it is a cumulative probability of reaching the barrier before T at current time t. Note that as V_t becomes large, the likelihood of the barrier being activated becomes negligible.[8]

To derive the option value, based on the formula for a European down-and-out call option proposed by Broadie et al. (1997), I need the solution of diffusion Equation [2-8] with the initial condition $A(0,x) = F(e^x)$.[9] When

$$A(\tau, x) = \frac{1}{\sqrt{2\pi}}\int_{-\infty}^{\infty} F(e^{x+\sigma\sqrt{\tau}\xi})e^{-\frac{1}{2}\xi^2}d\xi \qquad [2\text{-}8]$$

then

$$C(t,V) = V\left[N(d_1) - \beta^{\frac{2r}{\tilde{\sigma}^2}+1}N(d_3)\right] - Ie^{-r(T-t)}[N(d_2) - \beta^{\frac{2r}{\tilde{\sigma}^2}-1}N(d_4)] \qquad [2\text{-}9]$$

where

$$d_1 = \frac{ln\left(\frac{V}{I}\right) + (r + \frac{1}{2}\tilde{\sigma}^2)(T-t)}{\tilde{\sigma}\sqrt{T-t}}, d_2 = d_1 - \tilde{\sigma}\sqrt{T-t} \qquad [2\text{-}10]$$

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8 Many models on credit default (e.g. Reisz and Perlich, 2007) also include a second probability that the asset price is between B and I, i.e. $B \leq V_T < I$.

9 Appendix A.1 contains the detailed proof.

$$d_3 = d_1 + \frac{2}{\tilde{\sigma}\sqrt{T-t}} ln(\beta)\, , d_4 = d_2 + \frac{2}{\tilde{\sigma}\sqrt{T-t}} ln(\beta). \qquad [2\text{-}11]$$

2.3.2.2 Compound barrier options

Multi-stage investments can be seen as a sequence of real options and thus modelled as an N-fold compound option (Cassimon et al., 2004). For an investment project with three phases (I, II and III), as is used in our case study, the pilot phase I has a strategic value as it provides the option to move to phase II in the case of success, which in itself gives the option to move to phase III.

The start of phase I indicates the opportunity to subsequently invest in two optional phases towards the full commercialization of the fuel station network.[10] The strategic value of this opportunity can be captured by a 2-fold compound option given by:

$$C_2(t,V) = V\left[N\left(a_1, a_2;\ \sqrt{\frac{T_1}{T_2}}\right) - (\frac{B}{V})^{\frac{2r}{\tilde{\sigma}^2}+1} N\left(c_1; c_2; \sqrt{\frac{T_1}{T_2}}\right)\right] - I_2 e^{-r(T_2-t)}[N\left(b_1; b_2; \sqrt{\frac{T_1}{T_2}}\right) -$$

$$(\frac{B}{V})^{\frac{2r}{\tilde{\sigma}^2}+1} N\left(d_1; d_2; \sqrt{\frac{T_1}{T_2}}\right)] - I_1 e^{-r(T_1-t)}[N(d_1) - (\frac{B}{V})^{\frac{2r}{\tilde{\sigma}^2}+1} N(d_1)], \qquad [2\text{-}12]$$

where C_2 is the value of the compound option with the notations:

$$a_1 = \frac{ln\left[\frac{V}{V^*}\right] + \left(r + \frac{1}{2}\tilde{\sigma}^2\right)(T_1 - t)}{\tilde{\sigma}\sqrt{T_1 - t}}, \qquad a_2 = \frac{ln\left[\frac{V}{I_2}\right] + \left(r + \frac{1}{2}\tilde{\sigma}^2\right)(T_2 - t)}{\tilde{\sigma}\sqrt{T_2 - t}},$$

$$b_1 = a_1 - \tilde{\sigma}\sqrt{T_1 - t}, \qquad b_2 = a_2 - \tilde{\sigma}\sqrt{T_2 - t}\,, \qquad c_1 = a_1 + \frac{2}{\tilde{\sigma}\sqrt{T_1 - t}} ln\left[\frac{B}{V}\right],$$

$$c_2 = a_2 + \frac{2}{\tilde{\sigma}\sqrt{T_2-t}} ln\left[\frac{B}{V}\right]\, , d_1 = b_1 + \frac{2}{\tilde{\sigma}\sqrt{T_1-t}} ln\left[\frac{B}{V}\right], \ d_2 = b_2 + \frac{2}{\tilde{\sigma}\sqrt{T_2-t}} ln\left[\frac{B}{V}\right]. \qquad [2\text{-}13]$$

In this model T_1 is the maturity date of the first option. At time T_1, the compound option gives the right to buy another option C_1, the underlying option that has an exercise price of I_2 and a maturity date T_2. V^* is the value that the underlying option C_2 is at the money at time T_1, i.e., $V(T_1) = V^*$. The solution of V^* solves the underlying call option $C_1(T_1) - I_1 = 0$. For this multi-stage investment to

[10] It is straightforward to extend the model to more phases.

successfully move to investment phase III, the boundary condition that $V(T_2) > I_2$ given that $C_1(T_1) > I_1$and $V_t \geq B$ needs to be fulfilled. It follows in a straightforward way that the value of the compound call option C_2 depends on the joint probability that the project value is above V^* at T_1 and above I_2 at T_2, conditional on staying above barrier B during the two optional phases.

2.4 Case Study

This section applies the compound barrier option model to the case of technological innovation in hydrogen fuel-stations in a region of the Netherlands. First, I provide some background information and describe the business case. Next, I give an overview of the input numbers and cash flow calculations before moving to the valuation through the compound barrier option framework.

2.4.1 Description of the hydrogen infrastructure project

According to the International Energy Agency, the transportation sector in 2009 consumed nearly 56% of global oil production and was responsible for around 50% of all airborne emissions (IEA, 2010). The combination of diminishing fossil energy resources, environmental pollution, and climate change urgently calls for a sustainable transport system. Unlike fossil fuel, hydrogen does not emit carbon dioxide, which can substantially reduce emissions of regulated pollutants and greenhouses gases (Ekdunge and Råberg, 1998; Gasafi et al., 2008). Being powered directly from hydrogen-oxygen reaction, fuel cell vehicles can achieve a high level of system efficiency in an extremely quiet operation process with zero tailpipe emissions (Smit et al., 2007). Sandy Thomas (2009) compared the societal benefits of deploying various alternative transportation solutions, including hybrid electric vehicles and all-electric vehicles powered by either batteries or fuel cells, leading him to conclude that a hydrogen powered fuel cell vehicle is the best option to reduce greenhouse gases. Mercuri et al. (2002) estimated that replacing 5% of the diesel buses in Milan with hydrogen fuel cell buses could reduce health care costs by € 1.37 million per year.

As an energy carrier, hydrogen cannot be directly extracted like natural gas or oil. Just as electricity, it has to be produced from a primary source and transmitted to the location of consumption. Consequently, existing transport infrastructures need to be upgraded to supply hydrogen fuel cell vehicles. This requires significant amounts of irreversible investment costs over a decade or more until large-scale commercialization can be reached. With a long maturity time, profitability is most likely to be delayed until a sufficient number of hydrogen-powered vehicles can be produced and accepted by consumer markets. The significant initial costs, together with the project uncertainty, will probably result in insufficient cash inflows to justify investment based on any traditional economic valuation model such as a cost-benefit or a NPV model. Based on the environmental and economic issues discussed, it is widely believed among practitioners that additional strategies and incentives are required to accelerate the transition.

A hydrogen energy chain starts with hydrogen production, followed by hydrogen transport and distribution, and finally hydrogen conversion and end use. The costs of a hydrogen infrastructure vary with different types of hydrogen production technologies, forms of storage, and methods of transportation and dispensing. Most of the infrastructure cost will be spent on building a large network of refuelling stations. I consider the most likely case where relatively large-scale centralized hydrogen production plants produce hydrogen, which will then have to be transported and distributed to the fuelling stations. Liquefied hydrogen will be transported by tanker trucks; the cost of which is incorporated in the production cost.

Our case study is based on the HyWays (2008) scenario. Hydrogen-based vehicle rollout in the Netherlands is expected to happen in three phases: a pre-commercial phase from 2010 to approximately 2014 comprised of technology refinement and market preparation. About 30 hydrogen stations will be set up to serve around 1000 cars. The early-commercialization phase II (2015-2024) requires the construction of additional fuelling stations up to a total of 100 stations serving approximately 5000 fuel cell vehicles. Finally, in the full-commercialization phase III (2025-2044) approximately 20,000 hydrogen vehicles will be on the road in this region, which will take approximately 350 hydrogen refilling stations.

In the remainder of this section, I will conceptualize the initial investment as creating growth options and develop a framework for the valuation process. I follow the HyWays scenario and assume that investment in a hydrogen infrastructure will take place in several phases, moving gradually from small-scale fleet projects to large distribution network coverage. The value of such staged investments is not only determined by the cash flows coming from the initial investment, but also by the future investment opportunities opened up by the pilot stage. Each stage can be viewed as an option on the value of subsequent stages and valued as a compound option (Cassimon et al., 2004). It is important to note that Phase III (full-commercialization) cannot proceed without the execution and successful completion of Phase II, which itself will only take place upon the successful transition from Phase I. The end points of Phases I and II thus represent decision times. A positive continuation decision at that time requires the option value of the future project to exceed the extra investment required to enter the next phase. If not, the project will be terminated. In addition, default in the early stages is possible between formal decision moments when the project value drops below the barrier. In that case, the entire project will be directly terminated.

2.4.2 Overview of the input parameters and cash flow calculations

To calculate the expected operating cash flows for each project phase, I need to estimate the present value of the expected operating revenues R_t less operating expenses C_t:

$$R_t = \sum_{t=1}^{T} F_t \cdot \partial \cdot X_t \cdot H_t \cdot e^{-rt} \quad and \quad C_t = \sum_{t=1}^{T} (F_t \cdot \partial \cdot X_t \cdot CU_t + I_t \cdot M + CL_t) \cdot e^{-rt} \qquad [2\text{-}14]$$

with T the estimated economic lifetime of the infrastructure, F the number of hydrogen fuel cell vehicles on the road, ∂ the fuel efficiency in kg per km, X the estimated annual travel distance in km per vehicle, H the hydrogen retail fuel price per kg (adjusted for fuel tax), CU the variable hydrogen production costs, M the fixed operational and maintenance costs per year expressed as a percentage of the investment cost I (the construction costs of the fuel stations), CL the average labour cost per year and r the risk-adjusted discount rate.[11]

Figure 2-2 gives an overview of the input values of all parameters of our cash flow model.[12] To calculate hydrogen demand for fuel cell passenger vehicles, I assume that each vehicle will use approximately 0.7 kg of hydrogen each day (CaFCP, 2008). For an average fuel cell vehicle with a fuel economy of 80 to 96 kilometres per kg, this would accommodate about 56 to 64 kilometres of driving on an average day (Ogden, 1999b; CaFCP, 2008). During the full commercialization phase with approximately 20,000 fuel cell vehicles on the roads, this corresponds to a total hydrogen fuel demand of $5{,}11 \times 10^6$ kg per year. For hydrogen fuel to be competitive with fossil fuels, the literature generally assumes a retail price of €10/kg (Benthem al., 2006).[13] Although hydrogen is much cheaper produced from natural gas, the production process is always associated with the emission of greenhouse gases and local pollutants (Haryanto et al., 2005). Sustainable hydrogen cost is initially about €5/kg, but due to technical learning, I assume it will decrease to a long-term production cost of €2/kg during the full commercialization phase (Benthem al., 2006). This includes all the relevant expenses, for instance, transportation to the refilling station and carbon capture and storage (CCS) costs if necessary. All the numbers in Figure 2-2 are expressed in 2010 euros and are adjusted for inflation in the cash flow calculations. For these computations, I use a 25.5% marginal tax rate (KPMG, 2011), an average

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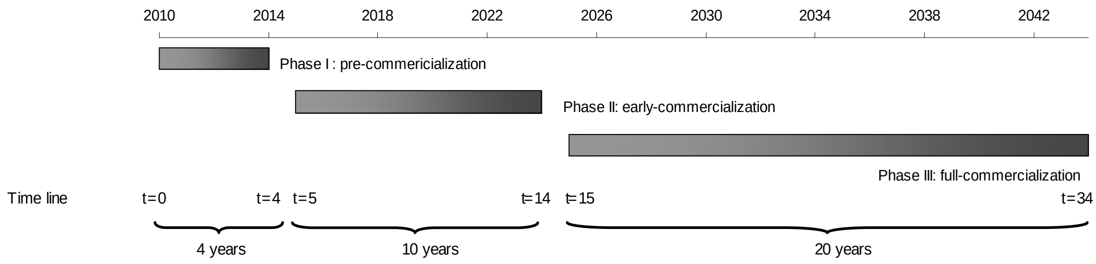
[11] The full structure of the cash flow model is graphically presented in appendix A.2.

[12] Where necessary, we use secondary sources to determine appropriate parameters for this case.

[13] We take into account the regular fuel taxes in the Netherlands such as excise duty and VAT, which lowers the net retail price to €4/kg.

Eurozone inflation rate of 2.24% (ECB, 2011), a 21.21% net working capital requirement in a given year (as percentage of the sales) (Damodaran, 2011), and a straight-line depreciation over the 20-year economic life of each station. I use a risk-adjusted discount rate of 8% for calculating the NPV of the project cash flows.[14]

Figure 2-2: Overview of the hydrogen infrastructure case study with main input parameters



Parameter	*phase I*	*phase II*	*phase III*	*source*
# Stations	30	100	350	HyWays (2008)
# FCVs	1,000	5,000	20,000	HyWays (2008)
Consumption/year (kg)	255.5	255.5	255.5	CaFCP (2008)
H(€/kg) (pre-tax)	10	10	10	van Benthem et al. (2006)
C(€/kg)	5	5	2	van Benthem et al. (2006)
CL(mln/year)	0.32	0.32	0.32	HyWays (2008)
Mainten.coeff.	2.7%	2.7%	2.7%	HyWays (2008)
Inflation	2.24%	2.24%	2.24%	website ECB (2011)
Tax rate	25.5%	25.5%	25.5%	website KPMG (2011)
WACC	8%	8%	8%	website Damodaran (2011)
Depreciation (year)	5%	5%	5%	Dutch tax code (2011)
NWC/Sales	21.21%	21.21%	21.21%	website Damodaran (2011)

Each stage also requires investments in the necessary amount of hydrogen fuel stations in order to operate the fuel network. The cost of a hydrogen fuel station depends upon many factors, including the type of station, location, equipment manufacturing volume and continuing technology advancements. In the case study, I use the CGH2 fuel station type from the HyWays project with a unit cost of approximately €0.49 million. I assume unit investment costs can decrease over time as a result of economies of scale and learning. To reflect this, I specify the cost function as $\omega(N) = \alpha \cdot N^{-b}$, where $\omega(N)$ is the investment cost of the N-th unit, b is a learning parameter and α the investment cost of the first unit (€0.49 million). The average investment cost to build N fuel stations will therefore be equal to $I = \alpha \cdot \int_1^N N^{-b} dN$. To simplify calculations, the construction costs are assumed to occur at the beginning of each phase: €12.52 million for the first phase in year 2010, €26.01 million for the second

[14] This cost of capital corresponds to the 2010 sector averages of oil and gas distribution (7.19%), environmental (7.62%), natural gas (8.07%), power (8.23%), automotive (8.58%) and chemical (8.88%). Numbers are taken from Damodaran (2011).

phase in 2014 and €85.22 million for the third phase in 2024.

Table 2-1 gives a concise overview of the project's cash flows.[15] The construction costs in the subsequent phases rise strongly due to the increasing number of fuelling stations to be built, from 30 in phase I, to 100 in phase II and 350 in phase III. The gradual reduction in the unit production costs only provides some moderation of the total investment required. Net operational cash flows remain negative in phases I and II and only turn positive in phase III. Even phase III as a stand-alone project is unprofitable, however. In NPV terms in 2024, required investment is €85.22 million while expected net cash flows from 2024 till 2044 – conditional on the available information in 2010 – only equals €38.97 million. I find a -€14.31 million NPV for phase I as a stand-alone project and a -€56.90 million NPV for the entire three phase project. Based on an NPV framework, the project will be clearly rejected. Even the pilot phase will not be started. That is, from an NPV point of view, no feasible business case exists for the development of a hydrogen-based transportation system in the Netherlands, despite the societal desirability of a more sustainable transportation system in the future. Put differently, according to our computations, a minimum government subsidy of €14.31 million would be required for the pilot to start.

Table 2-1: Project's Cash Flows (in € mln)

	NPV (2010)			**NPV (2014)**		**NPV (2024)**	
	Total	Investment	Net CF	Investment	Net CF	Investment	Net CF
Phase I (2010-2014)	-14,31	-12,52	-1,78				
Phase II (2014-2024)	-26,85	-19,12	-7,73	-26,01	-10,52		
Phase III (2024-2044)	-16,42	-29,02	13,27			-85,22	38,97
Total	**-56,90**	**-60,66**	**3,09**				

The next section analyses the same business case from a real option framework and will provide additional insights into the flexibility of a phased investment project. It will show under what conditions each phase will be terminated and under what conditions investment in the pilot phase will be triggered.

2.4.3 Option Valuation

I start our real option valuation using the parameters from Figure 2-2 that were also used for the NPV

[15] A more detailed overview of the cash flow calculations is available from the authors upon request.

computation. Investing in pilot phase I opens up the possibility for two sequential follow-up phases II and III. The option on this sequential option can be seen as an N-fold compound option (multi-stage project valuation). A compound option model requires the input of the investment costs per phase (I_1, I_2 and I_3), the present value of the expected cash flow upon full-commercialization V_0, and an estimate of the volatility of the project return $\tilde{\sigma}$. As I combine the compound option framework with a barrier option, our model also requires the input of the barrier B. In this section, I propose benchmark parameter values for B and $\tilde{\sigma}$ as well as investigate to what extent variation in these parameters influences the results.

As exemplified by Equation [2-2], our model collapses market and technological uncertainty into one volatility metric $\tilde{\sigma}$. I propose to use available market data to provide a plausible estimate of this overall volatility. To this purpose, I select four listed small-cap firms and use the average of their stock price volatility as a proxy for our project volatility. The chosen firms are Hydrogenics Corp, Ballard PoIr Systems Inc, Fuel Cell Energy Inc and Plug PoIr Inc respectively.[16] They have been selected because (a) they are active in the segment of hydrogen fuel cells and hydrogen fuel stations, (b) they are comparable in size to our project, (c) as small-caps their stock returns should reflect shocks to their firm value more accurately than would be the case for larger, more diversified firms and (d) their standard deviation in firm value should reflect the impact of both market and technological risk. Based on the daily stock returns over the period 2005-2009, adjusted for dividends and stock splits, I obtain an average annual project volatility of 66.75%, assuming 250 trading days per year.[17] [18]

Finally, I need to determine the level of the barrier. Using a data set of 7,787 firm-years on a diverse set of industrial firms, Brockman and Turtle (2003) find an implied barrier of about 70% for the total sample. However, different barriers have been suggested in the literature. For example, firms with high asset variability or high financial leverage can be expected to have a relatively high probability of hitting the barrier before the expiration date of the real option. This reflects the different position and trade-offs between debt-holders and shareholders. Debt-holders can have an incentive to enforce bankruptcy of the project before the next phase or decision point has been reached. Wong and Choi (2009) find that the median firm has a default barrier at around 74% of its liabilities. Given that project companies have an average debt-to-total capitalization ratio of 70% (Esty, 2004), this would imply a

[16] I refer to Appendix A.3 for more qualitative and quantitative details about these firms.

[17] I follow the approach of Damodaran (2011) and assume that the standard deviation of debt is one-third of the standard deviation of equity and that the correlation between stock and bond prices is 0.30.

[18] Compared to industry averages for 2010 our project volatility estimate is higher than the averages of oil and gas distribution (37.77%), natural gas (38.29%), automotive (46.72%) and power (56.52%) and of similar magnitude as chemicals (66.53%) and environmental (67.65%). See Damodaran (2011).

barrier of 51.8% in our application.

In our analysis, I therefore use both a 50% barrier and a 70% barrier B of the project value and compare it to the benchmark no-barrier real option model. Using Table 2-1, the barriers then equal €6.64 million and €9.29 million, respectively. If the project value drops below this value before reaching the next phase, investors will pull the plug and terminate the project. When I put the above parameters in our compound barrier option model, I obtain the results as presented in Table 2-2.

Table 2-2: Project valuation for different barriers

Scenario	V_0	Barrier	NPV Project	NPV Rule	Value Compound Option	Required Investment Phase I	Real Option Rule
No barrier	13.27	0	-56.9	Reject	11.11	14.31	Reject
$B = 50\% V_0$	13.27	6.64	-56.9	Reject	7.86	14.31	Reject
$B = 70\% V_0$	13.27	9.29	-56.9	Reject	4.37	14.31	Reject

Legend: All numbers in million euros, except retail price. The pre-tax retail price equals €10 in all scenarios. The corresponding after-tax retail price equals €4. Project volatility is assumed to equal 66.75% on an annual basis.

All three option models reject the investment, similar to the NPV rule. However, while the NPV rule shows a significant negative NPV value of €-56.9 million, the no-barrier option has a value of €11.11 million, short only about €3 million of the acceptance threshold. Here, the threshold is equal to the investment cost required for the pilot phase I of the project (€14.31 million, see Table 2-1.[19] Obviously, the follow-up potential of phases II and III is insufficient to justify investment in phase I.

The impact of imposing a barrier is also clear from the table. Imposing a 50% barrier reduces the option value to €7.86 million and a 70% barrier reduces it to €4.37 million. The barrier makes the project increasingly unattractive, corresponding to the higher likelihood of an abrupt and permanent knock-out. Applying Equation [2-7], it follows straightforwardly that the probability of hitting the 50% barrier prior to the full implementation phase equals 19%, and of hitting the 70% barrier 54%. With a high probability of project default, the upside potential of phase II and III is too small to induce firms to invest in the pilot phase necessary to develop a hydrogen fuelling station network. Note that our result confirms the general message in the literature that hydrogen, as a sustainable transportation mode, needs government support for the initial take-off (Schulte et al., 2004; Murthy et al., 2011; Soest, 2005).

[19] In our real option computations, I add the NPV of negative operational cash flows in phases I and II to the required investment at the start of each phase for simplicity.

Subsequently, I analyse to what extent financial government support may turn the infrastructure project into a profitable business case, inducing firms to invest in the pilot phase. Naturally, the government has many instruments at its disposal to provide stimulus to the private sector in starting off the pilot phase of the project, such as providing a lump-sum subsidy, becoming a subordinated investor in the project itself, or granting various transitory or permanent tax exemptions (van Soest, 2005). Here, I limit us, for illustrative purposes, to varying degrees of excise duty discounts. Moreover, I assume the benefits of these discounts accrue to the producer rather than the consumer, as the consumer retail price is assumed to remain constant. Alternative scenarios are also possible.

In the base case of Table 2-2, a pre-tax retail price of €10 per kg of hydrogen corresponded to an after-tax retail price of €4 per kg. The 60% fuel tax burden is of similar magnitude as of fossil fuel and consists of a combination of excise duties and VAT. Under a similar fuel tax regime as fossil fuels, both the NPV and the real option model reject investment in the infrastructure project. I consider discounts of 25, 50, 75 and 100 percent of the excise duties on fuel. In Table 2-3, I demonstrate the effect of these discounts on the attractiveness of the project. Note that both V_0 and the required investment in phase I depend on the tax regime. In the latter case, this results from the fact that I add the operational cash flows from phase I to the investment cost for simplicity. With lower taxes, these cash flows become slightly less negative and thus reduce the required investment in phase I.

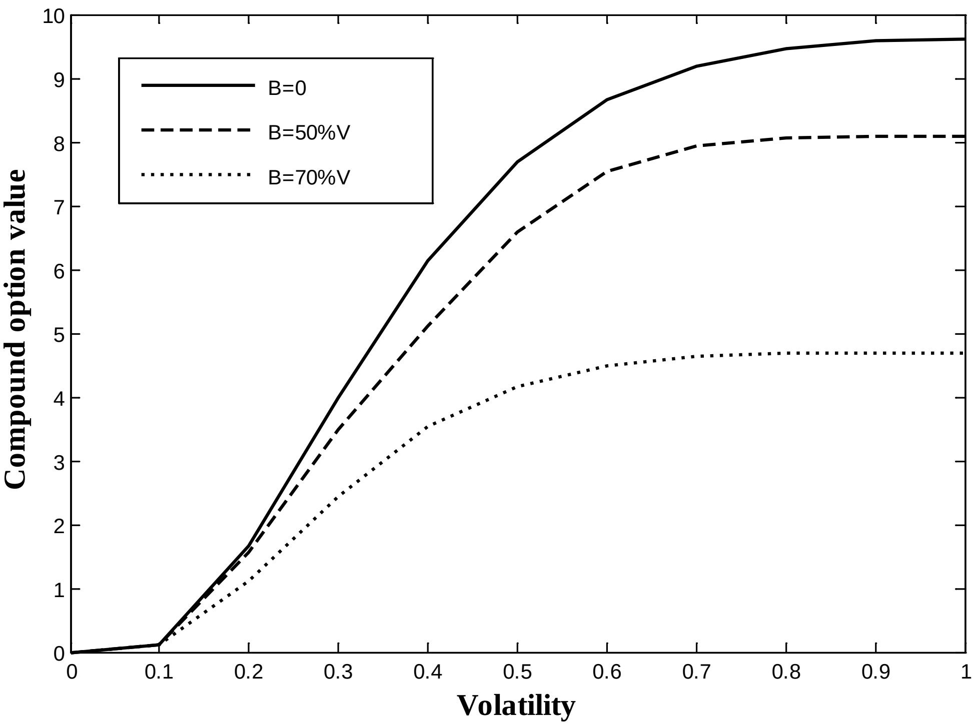
Table 2-3: Project valuation with fiscal subsidy (discount on excise duties)

Tax Scenario	**After-tax Retail Price**	**V_0**	**Barrier**	**NPV Project**	**NPV Rule**	**Option Value**	**Required Investment Phase I**	**Real Option Rule**
No barrier								
25% discount	5.1	26.38	0	-39.8	Reject	23.25	13.92	Accept I
50% discount	6.2	39.50	0	-22.6	Reject	35.66	13.53	Accept I
75% discount	7.3	52.61	0	-5.5	Reject	48.20	13.13	Accept I
100% discount	8.4	65.73	0	**+11.7**	Accept	60.84	12.74	Accept I
50%barrier								
25% discount	5.1	26.38	13.19	-39.8	Reject	11.30	13.92	Reject
50% discount	6.2	39.50	19.75	-22.6	Reject	16.26	13.53	Accept I
75% discount	7.3	52.61	26.31	-5.5	Reject	24.05	13.13	Accept I
100% discount	8.4	65.73	32.87	**+11.7**	Accept	40.94	12.74	Accept I
70% barrier								
25% discount	5.1	26.38	18.47	-39.8	Reject	8.79	13.92	Reject
50% discount	6.2	39.50	27.65	-22.6	Reject	12.27	13.53	Reject
75% discount	7.3	52.61	36.83	-5.5	Reject	17.73	13.13	Accept I
100% discount	8.4	65.73	46.01	**+11.7**	Accept	28.63	12.74	Accept I

Legend: All numbers in million euros, except retail price. The pre-tax retail price equals €10 in all scenarios. Project volatility is assumed to equal 66.75% on an annual basis.

The differences between the NPV framework and the three real option model become quite evident now: under the NPV rule, the project only turns profitable when no excise duty is imposed at all. The real option framework shows a more favourable trade-off. Without a barrier, a 25 percent discount is quite sufficient to make investment in the pilot phase attractive. If the barrier equals 50 percent, the project is still rejected at a 25 percent excise discount, but easily accepted at a 50 percent discount. Finally, with a 70 percent barrier, a 50 percent discount is not sufficient but a 75 percent is. Overall, the computations suggest tax incentives can be structured in a way to sufficiently support the development of a hydrogen infrastructure.

Figure 2-3: Effect barrier level on option value and total volatility



Finally, I turn to the role of project volatility. Generally, in standard real option models higher volatility implies a higher option value as the probability of ending in the money increases. However, in the case of a barrier there is a countervailing force: higher volatility raises the probability of hitting the barrier and seeing the project fail permanently.

Figure 2-3 demonstrates the effect of different project volatilities on the compound option value for barrier levels B of 50% and 70%, respectively, compared to the no barrier benchmark case. Generally, the lower the barrier and the lower the project volatility, the stronger the positive link between project volatility and option value. In the range of plausible project volatilities, the negative effect of hitting the barrier roughly offsets the positive effect of higher potential values. Overall option values appear relatively insensitive to changes in project volatility in this range.

2.5 Market Feedback and Real-World Implications

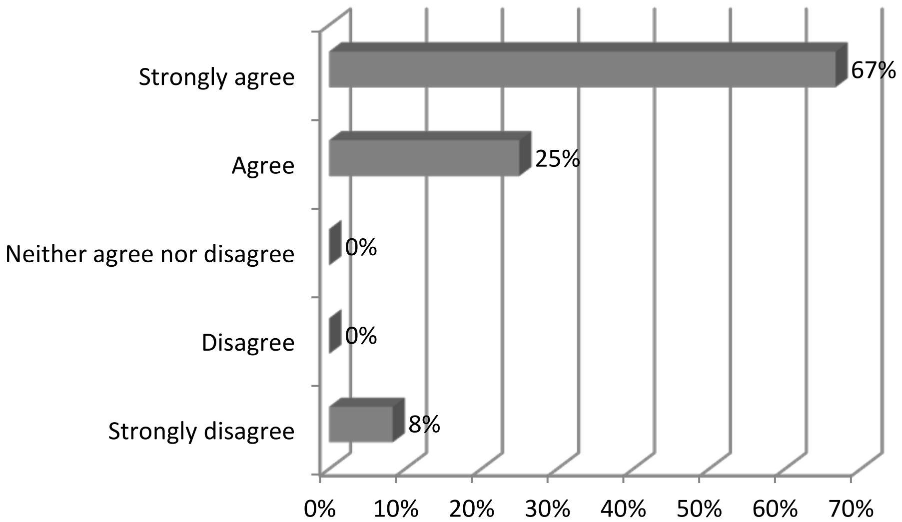
The main result of our case study is that hydrogen infrastructure investments may not pay off without any commitment of governmental schemes. To assess the degree of realism of our findings, I subject them to business practitioners' expectations. To this purpose, I reached out to the business community by means of a small-scale survey targeted at investors, businesspersons, engineers and government agency officials. Our sample of practitioners was constructed through a structured search on the social media website LinkedIn using keywords ‘hydrogen’, ‘fuel cells’, ‘renewable energy’ and ‘sustainable energy’. I distributed our study to 63 individuals and asked them to answer three questions related to our findings. The three questions had a closed format and used a five-point Likert scale. I communicated to them that I will not report individualized and identifiable answers, but only aggregate results. I also asked for their personal opinion, not for the official viewpoint of the organization they are working for, in order to avoid strategic answers. The response rate was about 40 percent. While I do not want to claim formal representativeness of the survey, the response rate seems sufficient to at least provide some suggestive evidence on the realism of our analysis.

First, I asked practitioners’ feedback on the statement:

“In order for a hydrogen infrastructure network to take off in the next 5-10 years, significant governmental support is needed.”

The overwhelming majority of the respondents agreed (25%) or strongly agreed (67%) with this statement for the need of significant government support (see Figure 2-4). This outcome is consistent with our case study finding that investment in a network of hydrogen fuelling stations is unprofitable without serious governmental commitment. The business community seems to strongly call for governmental support, as they do not see private investors committing significant resources to such infrastructure projects.

Figure 2-4: Market feedback on government intervention



Question: In order for a hydrogen infrastructure network to take off in the next 5-10 years, significant governmental support is needed.

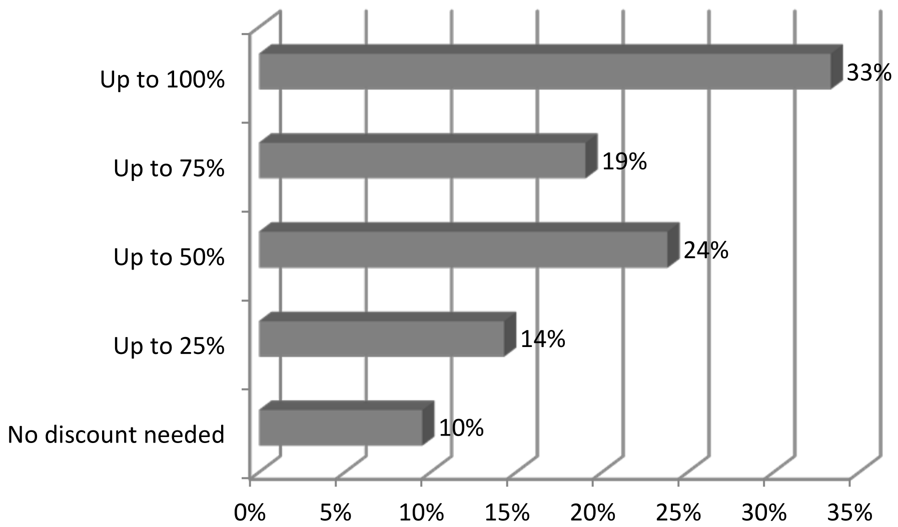
Legend: Survey among 63 practitioners in business, engineering and government agencies conducted in January and February 2015. Response rate amounts to 39.7%.

Next, I put the following statement to our survey participants:

"When the government would decide to stimulate the use of hydrogen as a car fuel through a discount on the excise duty, what is the amount of discount needed to induce?"

Again the large majority of the respondents (76%) called for substantial discounts on excise duties (see Figure 2-5). Twenty-four percent deem a discount up to 50% is necessary for hydrogen projects to become profitable, 19% expect a discount up to 75% to be crucial to stimulate private investment, while one third of the respondents call to fully waive all excise duties. The survey results confirm the case study findings which showed that a 50% to 75% discount was needed to turn the hydrogen infrastructure project profitable.[20]

Figure 2-5: Market feedback on excise duty discount



Question: When the government would decide to stimulate the use of hydrogen as a car fuel through a discount on the excise duty, what is the amount of discount needed to induce?

Legend: Survey among 63 practitioners in business, engineering and government agencies conducted in January and February 2015. Response rate amounts to 39.7%.

Finally, I asked for a direct comparison of our findings with the opinions of the respondents. To give the participants with a good view of our results, as well as the approach used to obtain them, I provided them with a short management summary and then asked the following question[21]:

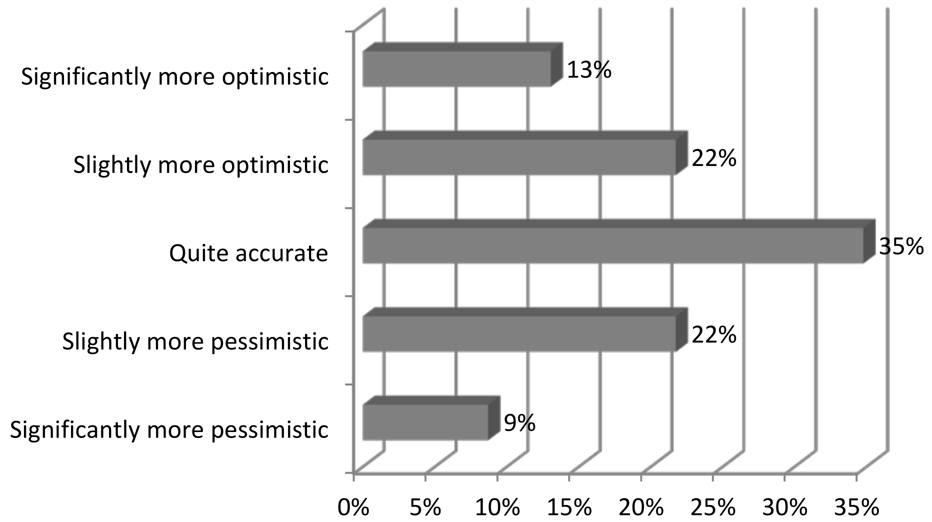
[20] In a follow-up conversation with one respondent, he or she indicated that a discount on excise duties alone would be insufficient and he or she called for direct government subsidies in the construction cost of the fuelling stations. The respondent argued, "at this moment a first network of a dozen of stations is constructed in California with a government subsidy of about 85% of the initial investment costs."

[21] This summary stated: "Our case study is built upon the Hyways scenario and assumes three phases

"If you compare our expectations on the profitability of hydrogen infrastructures with your expert opinion on market developments in the hydrogen sector, our estimates are …"

The distribution of survey answers appears neatly centred around our case estimates. The largest group of respondents (35%) considers our estimates quite accurate. 35% considers our estimates slightly or significantly more optimistic, while another 31% considers our estimates slightly to significantly more pessimistic. Obviously, quite some heterogeneity exists in practitioners' expectations on market developments, probably showing the large degree of uncertainty. However, it is comforting to see that our findings are actually quite close to the median view. In a follow-up with a few respondents, one respondent stated, "[your] long term hydrogen production cost is too optimistic in my view. Something like 5 to 7 euros would be more realistic." Such an assumption would clearly raise the project's cost structure rendering the project even more of a loss loss. Another respondent was more optimistic about the number of hydrogen cars per station, which would increase the incoming cash flows of the project. A third respondent synthesized both views by stating that "some estimates could indeed turn out to be more optimistic in reality, while some would be more pessimistic", but "overall, one could say that one ends up in the middle again and that the case study's estimate are quite accurate."

Figure 2-6: Market feedback on modelling assumptions and outcomes



Question: If you compare our expectations on the profitability of hydrogen infrastructures with your expert opinion on market developments in the hydrogen sector, our estimates are...

Legend: Survey among 63 practitioners in business, engineering and government agencies conducted in January and February 2015. Response rate amounts to 39.7%.

(pre-commercialization – 5 years; early commercialization – 10 years and full commercialization – 20 years). I assume 30, 100 and 350 fuel stations respectively for each phase. I further assume a retail price of 10 euro per kg and a long-term production cost of 2 euro per kg. Under these assumptions I find that the entire project is loss-making. Only with significant reductions in the level of excise duties, the project becomes profitable." Respondents were also provided the full paper.

2.6 Conclusion

In this chapter, I contribute to the literature by including a knock-out barrier option in an N-fold compound real option model to take account of immediate project failure in a multistage investment context. The barrier is defined as a minimum constraint, of which the investor is not willing to fall short. While barrier options have become quite common in the financial option theory, applications of barrier-type options in a real investment setting are non-existent so far. In our view, the possibility of sudden failure in large infrastructural investment projects or in the development of innovative technologies should be taken quite seriously. Inappropriately ignoring the possibility of sudden failure can have large and adverse consequences for investment decision-making. While NPV computations may undervalue uncertain investment projects and unduly lead to project rejection, real option models that fail to account for the real-life possibility of intermediate project failure may lead to overvaluation and undue acceptance. Earlier attempts to deal with such phenomena use a Poisson process reflecting the probability that the project value jumps to zero or discrete failure probabilities at each stage of a compound option framework. I provide an alternative barrier approach to cope with this type of situations, which is both more realistic, as it does not depend on the occurrence of a catastrophe, and more elegant as, it allows for a closed-form solution.

I apply the model to the case of hydrogen infrastructure development. Despite the theoretical attraction of a zero-emission hydrogen energy economy, the development of a new hydrogen energy infrastructure is often seen as an insurmountable technical and economic obstacle to the use of hydrogen as an energy carrier. A future hydrogen transition relies on strategic planning and necessary investments: energy, economic and environmental analyses must be undertaken in concert with research in improved production, storage, and distribution technologies. To assist the transition, an adequate valuation approach is vital. Indeed, commercializing a new technology requires a revolutionary change from technological and market aspects; one might not anticipate the best path forward from the very beginning. No amount of planning and research can be trusted to reveal all contingencies and contingent probabilities from the start. For this reason, the use of a compound real option model where new information along the development path allows for reconsideration and reassessment is an attractive approach. Including an additional barrier option to reflect the possibility of project failure is appropriate in our view. However, it also makes valuation more complex as the project (option) value becomes path-dependent. Moreover, the extra boundary condition reduces the project value below that of the no-barrier benchmark option. As such, decision-making becomes more conservative and more often leads to rejection.

In our case study, I use a number of different external sources to set the parameters in the model.

Subsequently, I compute the project value for the hydrogen infrastructure project in the case of a barrier of 50 and 70 percent respectively of the NPV of the project cash flows in the full commercialization phase, and benchmark it against valuation through an NPV model and a no-barrier real compound option model. I find that even for the least conservative valuation method, the no-barrier option model, no profitable business case can be made for the development of hydrogen as a sustainable transportation mode. This is consistent with earlier literature. Note though that all three real option models are much closer to the acceptance threshold imposed by the first phase investment costs than the NPV valuation. Subsequently, I provide some suggestive scenarios that plausible tax schedules can be designed to overcome the starting problems for hydrogen infrastructure development. A 25 percent excise duty discount is sufficient for a positive decision in the no-barrier framework. For the 50 percent barrier, one needs a discount between 25 and 50 percent, and for the 70 percent barrier a tax discount of somewhat over 50 percent.

Finally, I confront our findings with the expectations from practitioners in the business world. The survey results are consistent with our case study findings. Practitioners strongly call for governmental support in order for hydrogen infrastructure investments to have any viability. The large majority of the respondents also call for large discounts on excise duties in line with our numerical simulations. To the extent that sudden project failure would be predominantly caused by potential reversals in political support, a cheap way to make the development of hydrogen infrastructure – and other similar projects – more attractive would be to design credible long-term political commitments to this type of development.

Chapter 3
Jump Diffusion Characteristics of Real Option Models

3.1 Introduction

Over the past decades, real option modelling has become an increasingly popular approach for the valuation of large infrastructure projects as well as the valuation of innovative projects in technology-intensive industries. Real option modelling starts with the choice of an appropriate stochastic process and a mathematical formulation of this process. The stochastic process chosen to govern the project value's development should ideally reflect the specific character of the underlying uncertainty. Through stochastic simulation, one can create multiple pathways of prices, obtain a statistical sampling of these simulations, and make inferences on the potential pathways that the actual price may undertake given the nature and parameters of the stochastic process used to generate the time-series. The choice of stochastic process obviously is an issue of great relevance in asset valuation. Since the outcome of a real option model strongly depends on the assumptions regarding this stochastic process; an inappropriate choice may have considerable negative consequences for investment decisions.

The task of determining what is the most appropriate process to represent the main uncertainties in a specific case is usually not a trivial one. In some cases, these uncertainties have elements of more than one type of process. The Geometric Brownian Motion (GBM) model is the most commonly used process due to its simplicity and wide-range of applications; it serves as a sort of catch-all model. Most of the earlier real option models were developed under this assumption, also due to the availability of an analytical solution. However, researchers have frequently pointed out that in some situations, the GBM process fails to characterize parts of the uncertainty, for instance, when the project's value may be subject to large and sudden changes – jumps – in the underlying state variables. Examples are investments in pharmaceutical R&D (McDonald and Siegel 1986) or in renewable technologies. Types of jumps include technical innovations (positive jumps), failure (negative jumps), new regulatory decisions (positive and negative jumps), and competitive entry or arrival of substitute products (negative jumps). In such circumstances, stochastic jump models may be more appropriate as they can be tailored to particular characteristics of the project under consideration. Applications that incorporate a Poisson jump process typically assume that jumps occur with small probability, are mutually independent, and follow a Poisson distribution.

In practice, the link between the type of uncertainty and the preferred valuation model seems rather loose. Certainly, no one-to-one relation between the specific type of uncertainty shock types and the choice of model exists. For instance, when I consider the literature on "investment cost uncertainty" I find applications using GBM models, controlled diffusion processes, jump processes and binomial lattices. It raises the question of how sensitive the choice of the stochastic model actually is. To our knowledge, little empirical evidence in the literature exists that provides information on the sensitivity of investment decision making to the stochastic model chosen, a notable exception being Martzoukos and Trigeorgis (2002).

This chapter aims at contributing to the literature by investigating the robustness of a real option valuation under different stochastic processes. I will limit our analysis to jump diffusion models and standard Brownian Motion models. Within the class of jump diffusion models, I allow for asymmetric – positive or negative – and symmetric jumps. In the analysis, I start from the option pricing framework developed by Martzoukos and Trigeorgis (2002). To allow for a valid comparison between the different stochastic processes, I impose constraints that make their trend return and total volatility equal. Subsequently, I price European options according to both stochastic models for a wide range of parameters characterizing the jump processes. Overall, I observe that in the presence of asymmetric jumps, the corresponding approximate GBM model tends to under-price relative to the jump model in the case of positive jumps and to overprice in the case of negative jumps. Put differently, approximating an asymmetric, skewed, stochastic process by a symmetric one does lead to systematic biases. However, I also conclude that the difference in option valuation remains limited, provided the appropriate constraints are imposed to warrant a valid comparison. This latter issue is of crucial importance. When both negative and positive jumps are present in a symmetric way, I find that the pricing difference between the true jump model and the approximate GBM model is generally small as the overpricing of the negative jumps and the under-pricing of the positive jumps to a large extent offset.

The chapter is set up as follows. In section 2, I provide a further motivation through a non-exhaustive literature review of real option modelling of technical uncertainty. I focus on three different branches of the literature on technical uncertainty, and show that within each branch a wide range of modelling approaches is used. I introduce the methodology in section 3, and section 4 elaborates on the research design to investigate the sensitivity of the choice of stochastic process and presents and discusses the call option valuation results. Section 5 summarizes and concludes.

3.2 Literature review

Technical uncertainty is more about technical parameters specific to natural resources investments, such as recoverable reserves and output rate of the project. Uncertainty about future project revenues is attached to output prices and considered a paramount concern (e.g. Siegel et al., 1987; Paddock et al., 1988; Pickles and Smith, 1993). Taking account of managerial control over the output rate, investors can respond by delaying production temporally or permanently depending on price levels and volatility. In this line of research, similar projects like copper mines (Cortazar and Casassus, 1998) or oil and gas (Paddock et al., 1988; Smith and McCardle, 1999) have also been widely applied by the real option approach. Over the years, the range of application has been substantially extended to other areas as well. Often real option models have been tailored to particular characteristics of investment projects like pharmaceutical R&D, renewable technologies, manufacturing and infrastructure developments. The term 'technical uncertainty' in the real options literature often refers to different types of uncertainty or different aspects of some source of technical risk. In this section I classify and summarize the literature into investment cost uncertainty, R&D technical uncertainty and external technical uncertainty.

The first type of technical uncertainty refers to investment cost uncertainty. In financial options, the exercise price is usually specified when the contract is entered into; this translates into knowing with certainty the cost of commercializing the project. In contrast, investment projects in architecture, engineering, construction and infrastructure often have an uncertain investment cost.

McDonald and Siegel (1986) studied the optimal timing to invest in a fuel plant project where the benefits from the project and the investment cost follow continuous-time stochastic processes. The valuation problem assumes that both the present value of benefits and the investment cost follow a Geometric Brownian Motion. In a similar vein, Zhao et al. (2004) presented a stochastic model for decision making of highway development, accounting for the evolution of traffic demand and land price. However, some researchers prefer applying a controlled diffusion process; they believe that uncertainty will be resolved through investment and the only way to uncover the true cost of exercise is to actually undertake the project. Pindyck (1993) pointed out this problem by slipping cost uncertainty into a technical dimension that relates to the true innovation effort needed to realize a project, and input cost uncertainty relating to the future prices of the resources needed. Following his research, Schwartz and Moon (2000) further applied this result in an R&D project, where they treated both the value of the underlying asset and the exercise price as stochastic. In a similar manner, Schwartz and Zozaya-Gorostiza (2003) developed two models for the valuation of information technology (IT) that account for uncertainty both in the costs and benefits associated with the investment opportunity. Indeed, such approach adds considerable realism to the modelling environment, but the complexity of the solution increases correspondingly when working in continuous time.

A second type of technical uncertainty refers to whether or not a technical solution or breakthrough for an R&D project or innovation will be reached. For instance, R&D projects within pharmaceuticals and biotechnology regularly feature technical uncertainty related to scientific discovery. In the drug development process, there is the inability of researchers to guarantee a priori safe and effective products that can pass clinical trial hurdles and gain FDA approval. In terms of modelling, there exist two streams of R&D technical uncertainty, symmetrical and asymmetrical. The symmetrical stream includes both technical breakthrough and failure; however, with asymmetrical R&D, technical uncertainty can either be positive only (technical progress) or negative only (failure).

Ott (1992) proposed that when both positive and negative Poisson processes govern an R&D investment, the investment remaining jumps to zero in case of R&D success, or the value of a failed R&D project drops to zero. In line with Brach and Paxson (2001), Wu and Yen (2007) used Merton's (1976) jump model to evaluate R&D projects. They hypothesized that the project value is a random variable and characterized the variation as jumps. Penning & Lint (1997) formulated such a model with the value of the underlying asset governed by stochastic jumps, plus a deterministic drift component, and have successfully applied it to R&D projects at electronics multinational Philips. Martzoukos and Trigeorgis (2002) studied jumps focusing on cases where the underlying asset follows a mixed jump-diffusion process involving various sources of jumps. Schwartz and Moon (2000) assumed that asset value volatility and cost uncertainty are standard Brownian diffusion processes, but that there is a possibility of a catastrophic failure represented by a Poisson process. Grenadier and Weiss (1997) modelled the arrival of sequential technological innovations as a Geometric Brownian Motion and assumed that when the process reaches a pre-specified level, a new technology becomes available for adoption. Huisman and Kort (2004) assumed technological progress follows a Poisson process so that at every point in time the probability that a new technology arrives is the same.

Finally, technical uncertainty can also refer to external sources of technical risk. Competition and some other uncertain factors are likely to cause the distribution of the future project value to become asymmetric. Higher project values are less likely to occur because of the potential competitive erosion of value. For some technology-intensive projects, technology uncertainty plays a dominant role in affecting investment timing. Kauffman and Li (2005) modelled the dynamics of competition between two technologies by making use of the first passage time of a stochastic process to characterize a random time in the future. Moreover, game-theoretical real options like in Huisman and Kort (2004) have also been applied to situations of the competitive dynamics between technology adopters significantly impacting their equilibrium investment strategies. For a general illustration of how the intersection of real options, game theory and the insights of the economic agents under uncertainty may refer to Grenadier (2000).

In this chapter, I focus on the R&D uncertainty type of technical risk and focus on the comparison of GBM versus different jump related models in continuous time.

3.3 Methodology

In the previous section, I discussed different types of technical uncertainty and different approaches to model such uncertainty. Ideally, the stochastic process chosen to govern the project value's development should reflect the specific character of the underlying uncertainty. Consequently, the choice of a correct stochastic process is an issue of great relevance in the asset's valuation aiming to represent uncertainties related to investments. However, the overview in section 2 suggests that in practice, the link between the prevailing type of uncertainty and the preferred valuation model is rather loose. Certainly, no one-to-one relationship between the specific type of uncertainty shock and the choice of model exists. To our knowledge, little empirical evidence in the literature exists that provides information on the sensitivity of investment decision making to the stochastic model chosen. Martzoukos and Trigeorgis (2002) provided some illustrative evidence about the degree to which a simple (Geometric Brownian Motion) diffusion process can approximate a single-class jump diffusion process.[22] Finally, Matsuda (2004) discussed the approximation of a Merton jump diffusion process with a standard Black-Scholes approach.

The issue of how different models compare with each other is particularly important, since each model differs fundamentally in its assumptions of the underlying structure of uncertainty. In this section, a common framework is set up to compare the pricing of different stochastic option models that are frequently used in the analysis of technical uncertainty. This allows us to evaluate relative performance in a consistent way. I will limit our analysis to jump diffusion models and standard Brownian Motion models. Within the class of jump diffusion models, I allow for asymmetric – positive or negative – and symmetric jumps.

I start from a mixed jump-diffusion process with various types of jumps, as proposed by Martzoukos and Trigeorgis (2002), henceforth MT, which takes the following form:

$$\frac{dV}{V} = \mu dt + \sigma dW_t + \sum_{j=1}^{J}(k_j \, dq_j). \qquad [3\text{-}1]$$

Equation [3-1] shows that the underlying project value V has an instantaneous expected return μ, and is driven by the Wiener process W_t whose innovations have mean zero and an instantaneous standard deviation σ. In addition, in this general specification there are J different sources of rare events (jumps). Each jump process j experiences a jump of size k_j when the jump counter dq_j equals 1, which

[22] Their derivation and analysis actually contains a mathematical error, so that their conclusions are invalid.

happens with probability λj; otherwise, dq_j equals 0. It is assumed that the stochastic shocks dW_t and dq_j are independent. Following Merton (1976), MT showed that a European call option on asset V can be valued as the discounted sum of the call option value conditional on any random realization of jumps multiplied by the probability of this specific jump realization. The sum over all possible jump realizations must then be taken.

Alternatively, I could think of the investment project as V being driven by a standard Geometric Brownian Motion, such as:

$$\frac{dV}{V} = \mu dt + \bar{\sigma} dW_t, \quad \text{[3-2]}$$

where the return process consists of a linear drift μ and a Wiener process representing "normal" price fluctuations. Innovations in the Wiener process W_t again have a normal distribution with mean 0 and an instantaneous standard deviation $\bar{\sigma}$. To value a European call option on this asset, I would use the standard Black-Scholes formula. In the following, I set up a simple experiment to check whether it matters if a European option on asset V is valued based on Equation [3-1] or [3-2].

First, returning to Equation [3-1], note that the actual trend of the process V does not equal the instantaneous drift μ, but also includes the value of the multiple jump processes, resulting in the following expression $\mu + \sum_{j=1}^{J} \lambda_j E[k_j]$, where E[.] represents the expectations indicator.

Obviously, this has consequences for an appropriate comparison between different option models and their valuation. MT argued that it makes sense to include so-called "compensation terms" to remove any trend effects of the jump processes. Assuming that the jump risk is diversifiable, they show that Equation [3-1] can be rewritten as

$$\frac{dV}{V} = (r - \delta^*)dt + \sigma dW_t + \sum_{j=1}^{N} (k_j \, dq_j), \quad \text{[3-3]}$$

where $\delta^* = \delta + \sum_{j=1}^{J} \lambda_j E[k_j]$, with δ equal to any form of dividend yield. In the remainder of the analysis, I will assume δ to be equal to zero. δ^* will be included and will be equal to the appropriate compensation term. I assume that each jump process j follows a Poisson process with parameter λj. The jump size k_j follows a stochastic process as well. I assume $1 + k_j$ to be log-normally distributed according to $\ln(1+k_j) \sim N(\gamma_j - \frac{1}{2}{\sigma_j}^2, {\sigma_j}^2)$, with $N(.)$ indicating a normal density function with mean $\gamma_j - \frac{1}{2}{\sigma_j}^2$ and variance ${\sigma_j}^2$. I will refer to γ as the jump size from now on and note that $E[k] = \exp(\gamma) - 1$. From the above, it follows that each jump process j, with $j = 1,\dots, J$ can be characterized by three parameters: the arrival probability λj, the mean jump size γj and the jump size standard deviation σj.

I start from the general situation where I have a European option with exercise price I and time to maturity T, and where the riskless real rate of interest equals r. Moreover, I assume that the realization of the number of jumps for each jump process up till time T is known. I refer to this as $n = (n_1, n_2, \dots, n_J)$, where n_j is the number of jumps for process j. The expected value of the option conditional on a specific realization of the vector n then can be written through a conditional version of the Black-Scholes model as:

$$E\left[\max\left(V_T - I, 0\middle|(n_1, \dots, n_J)\ jumps\right]\right.$$

$$= V_0\, exp\left[(r - \delta^*)T + \textstyle\sum_{j=1}^{J} n_j\, \gamma_j\right] N(d_{1n}) - IN(d_{2n}), \qquad [3\text{-}4]$$

where

$$d_{1n} = \frac{(ln\frac{V_0}{I} + (r - \delta^*)T + \sum_{j=1}^{J} n_j \gamma_j + \frac{1}{2}\sigma^2 T + \frac{1}{2}\sum_{j=1}^{J} n_j \sigma_j^2)}{\sqrt{\sigma^2 T + \sum_{j=1}^{J} n_j \sigma_j^2}}, \text{ and}$$

$$d_{2n} = d_{1n} - \sqrt{\sigma^2 T + \textstyle\sum_{j=1}^{J} n_j\, \sigma_j^2}.$$

To compute the unconditional discounted value of the option, the result of Equation [3-4] must be multiplied by the probability $P(n_1, n_2, \dots, n_J)$ of that specific jump realization. Subsequently this must be summed over all possible realizations and the appropriate discounting must be applied. Equations [3-5] and [3-6] display the corresponding formulas:

$$P(n_1, n_2, \dots, n_J) = \prod_{j=1}^{J} \left[\frac{e^{-\lambda_j T}(\lambda_j T)^{n_j}}{n_j!}\right] \ and \qquad [3\text{-}5]$$

$$c(V, I, T, \sigma, \delta^*, r, \lambda_j, \gamma_j, \sigma_j) =$$
$$e^{-rT} \sum_{n_1=0}^{\infty} \dots \sum_{n_J=0}^{\infty} \{P(n_1, \dots, n_J) * E\left[max(V_T - I, 0)\ |n_1, \dots, n_J)\ jumps\right]\}. \qquad [3\text{-}6]$$

I now turn to the issue of which specification of a standard Brownian motion model for V and corresponding option valuation would be an appropriate benchmark for the above multi-class jump process. Typically, the value of a European option based on the stochastic process for V_t in Equation [3-2] would be written as:

$$C = V_0 N(d_1) - I\ exp(-rT) N(d_2), \qquad [3\text{-}7]$$

where

$$d_1 = \frac{ln(\frac{V_0}{I}) + \left(r + \frac{1}{2}\bar{\sigma}^2 \right) T}{\bar{\sigma}\sqrt{T}} \ \ and$$

$$d_2 = d_1 - \bar{\sigma}\sqrt{T}.$$

I already briefly discussed the use of a compensation term to make sure that differences in trend effects dominate the results. From this discussion, I can conclude that option valuation based on the jump process in Equation [3-4] using $(\mathrm{r} - \delta^*)$ is comparable to option valuation of the corresponding Browning motion process using r (as shown in Equation [3-7]). A few points are important to note. First, for exactly symmetric jump processes – that is, opposite negative and positive shocks – for each jump process j with arrival probability λj, mean jump size γj and jump size standard deviation σj, there is also a jump process $j^*$with equal jump probability and standard deviation but with a mean jump size $\gamma_{j*} = -\gamma_j$. Second, one can think of this symmetric case as one in which the positive shocks are driven by one type of source, while the negative shocks come from a different source. Alternatively, one can think of it as shocks coming from one common source. Third, for a given realization of shocks until time T, positive and negative shocks do not need to offset ex post even though their ex ante likelihood is equal. Fourth, due to the nonlinearity of the log-normal process that drives the jump sizes, the compensation term, which equals the expected trend effect of the cumulative jump processes, will not be equal to zero even when the jump processes are modelled completely symmetrically.

Subsequently, the issue arises about which standard deviation $\bar{\sigma}$ in pricing Equation [3-2] and in the option price Equation [3-7] would appropriately reflect the combined uncertainty in the Brownian motion and jump processes of Equation [3-1] or [3-3]. MT argued that in the case where all J jump processes have the same parameters $(\lambda_j, \gamma_j, \sigma_j)$, the multi-class representation can be replaced by a single-class jump process with parameters $(\lambda_j, \gamma_j, \sigma_j)$. That is, instead of multiple identical jump processes, I now use one jump process with higher arrival probability. They then stated that this single-class jump-diffusion process can be approximated by a simple Brownian motion process (without jumps) with standard deviation $\bar{\sigma} = \sqrt{\sigma^2 + \sum_{j=1}^{J}(\lambda_j {\sigma^2}_j)}$. When applying this formula to the more general case with different jump processes – including both negative and positive shocks – they observed large deviations between the computed option values using Equation [3-4 to 3-6] on the one hand and [3-7] on the other. However, MT failed to take into account that the uncertainty around the mean not only is a function of the standard deviation σ of the Brownian motion in Equation [3-1] and the standard deviation of the jump size σ_j, but also of the expected jump size of individual processes. The more these deviate from zero, the fatter the tails of the resulting density function. Therefore, it is appropriate to use $\bar{\sigma} = \sqrt{\sigma^2 + \sum_{j=1}^{J}(\lambda_j {\sigma^2}_j + \lambda_j {\gamma^2}_j)}$ as the standard deviation in Equations [3-2] and [3-7]. Henceforth I will label this the augmented GBM approach.

In the next section, I will set up a framework for quantitative comparison of option values computed using Equations [3-4 to 3-6] and [3-7] respectively for different parameter settings $(\lambda_j, \gamma_j, \sigma_j)$ of the jump processes. This will allow an assessment of the importance of choosing the stochastic process that best reflects the specific character of the underlying uncertainty determining the project value's development.

3.4 Analysis and results

The choice of project characteristics in our setup is loosely related to the case of the development of hydrogen fuel cells in the Netherlands. I refer to Engelen et al. (2016) for a stylized description of this case. In general, the development of renewable energy technology is constrained by high R&D cost and difficulty of investment recovery, long and deferrable planning processes, high investment risks and uncertain returns (Lee and Shih, 2010). In particular, Chen et al. (2010) demonstrated that technologies for generating and storing hydrogen have not yet reached technological maturity, and the fuel cell technology is either in the mature stage or approaching maturity. This means that for the hydrogen case there are still large uncertainties associated with technological innovation. Obviously, this is a case where different assessments of the type and impact of technical uncertainties (technical breakthrough, competition, technical complexity, etc.) may lead to significantly different approaches to account for such uncertainty as well as to conflicting results.

Let V_0 represent the expected present value of the stream of profits related to the project - the introduction of hydrogen fuel cell driven cars – would generate once the infrastructure is in place. I assume V_0 to be equal to €85 million. The time to maturity of the option for this project is 20 years, or

80 quarters. The exercise price 20 years from now is assumed to equal €85 million as well. I set the risk-free interest rate r to be 0.25% per quarter, and assume the quarterly standard deviation of future cash flows to be 30 percent. The basic information is summarized in Table 3-1.

Table 3-1: Basic parameter values in valuation

Variable	Project's characteristics	Value
V_0	Present value of the underlying cash flow (in €mln).	85
I	Expenditure required in converting the investment opportunity into the option's underlying asset (in €mln).	85
T	The length of time the investment can be deferred without losing an opportunity (# quarters).	80
r	Risk free interest rate (quarterly)	0.25%
σ	Standard deviation (quarterly) of future cash flows	30%

For the analysis, I use three different settings. In the first, there is only one additional jump process that generates shocks with a positive expected value. In the second, there is only one additional jump process that generates shocks with a negative expected value. Both of these are asymmetric cases. On top of a symmetric source of uncertainty represented by the innovations of the Wiener process with standard deviation of 30 percent, there are either infrequent positive jumps – for instance technological breakthroughs – or infrequent negative jumps – technological failure. In the third, there are two jump processes that are symmetric with respect to their mean size so that both positive and negative shocks can occur. To investigate the sensitivity of the results to the choice of parameter values, $(\lambda_j, \gamma_j, \sigma_j)$ for the jump processes, I use different combinations of parameter values. For λ_j I consider jump probabilities of 1%, 3%, and 5% respectively per quarter. For mean jump sizes γ_j, I take values of 15%, 30%, 45% and 60% respectively. Finally, for jump size volatilities σ_j, I choose values of 0%, 10% and 20%. For each combination of parameter values, I compute both the option value when explicitly taking into account the specification of the jump process according to Equations [3-4] to Equation [3-6] and when approximating it through the augmented Brownian motion in Equation [3-7]. The results are in Table 3-2 to Table 3-4.

Table 3-2: Comparison of True process and GBM augmented with asymmetric positive jump model

	Jump size σ' = 0%		**Jump size σ' = 10%**		**Jump size σ' = 20%**	
	True process	**GBM augmented**	**True process**	**GBM augmented**	**True process**	**GBM augmented**
λ=1%,γ=+15%	71.25	71.24	71.27	71.26	71.33	71.32
λ=1%,γ=+30%	71.39	71.37	71.41	71.39	71.48	71.44
λ=1%, γ=+45%	71.66	71.57	71.68	71.59	71.75	71.64
λ=1%, γ=+60%	72.07	71.85	72.09	71.87	72.16	71.92
λ=3%, γ=+15%	71.34	71.33	71.39	71.38	71.57	71.54
λ=3%, γ=+30%	71.77	71.69	71.83	71.75	72.01	71.90
λ=3%, γ=+45%	72.53	72.28	72.59	72.33	72.77	72.48
λ=3%, γ=+60%	73.36	73.05	73.68	73.09	73.84	73.23
λ=5%, γ=+15%	71.42	71.41	71.52	71.50	71.80	71.77
λ=5%, γ=+30%	72.13	72.01	72.23	72.09	72.51	72.35
λ=5%, γ=+45%	73.34	72.94	73.43	73.02	73.70	73.25
λ=5%, γ=+60%	74.97	74.12	75.06	74.19	75.31	74.40

From Table 3-2, I observe that the augmented GBM process typically under-prices the call option relative to the jump process. The under-pricing increases with the mean jump size γ, the jump probability λ, and the jump size volatility σ. Within the grid of experiments, the degree of under-pricing remains limited and varies from almost zero to 0.91 (1.2 percent of the true call option price for the jump process) for the combination of parameter values $(\lambda, \gamma, \sigma)$ at the highest levels (at the bottom right of the table). Intuitively, the under-pricing can be explained by pointing to the fact that while the augmented GBM process does use the same overall measure of the project's volatility, it assumes this volatility to be symmetric. In contrast, the jump process has a skewed distribution with asymmetric positive shocks. The augmented GBM thus misses out on the high tail of the jump process, which becomes more pronounced with a higher jump probability and mean jump size.

A similar, but opposite picture emerges when considering only negative jumps. Table 3-3 shows that the augmented GBM now prices the option too high compared to the jump process. Again, the gap between the two prices increases with mean jump size, jump probability and jump size volatility. Higher values of either parameter makes the left – negative – tail more pronounced that the augmented GBM process fails to take into consideration to the full extent as it makes a symmetric approximation. The maximum gap is 0.72 (or 1 percent of the true call option value of the jump process).

Table 3-3: Comparison of True process and GBM augmented with asymmetric negative jump model

	Jump size σ' = 0%		Jump size σ' = 10%		Jump size σ' = 20%	
	True process	**GBM augmented**	**True process**	**GBM augmented**	**True process**	**GBM augmented**
λ=1%,γ=-15%	71.24	71.24	71.26	71.26	71.31	71.32
λ=1%,γ=-30%	71.35	71.37	71.36	71.39	71.41	71.44
λ=1%, γ=-45%	71.50	71.57	71.51	71.59	71.56	71.64
λ=1%, γ=-60%	71.69	71.85	71.70	71.87	71.74	71.92
λ=3%, γ=-15%	70.32	71.33	71.37	71.38	71.52	71.54
λ=3%, γ=-30%	71.63	71.69	71.67	71.75	71.81	71.90
λ=3%, γ=-45%	72.07	72.28	72.11	72.33	72.24	72.48
λ=3%, γ=-60%	72.61	73.05	72.65	73.09	72.75	73.23
λ=5%, γ=-15%	71.39	71.41	71.48	71.50	71.73	71.77
λ=5%, γ=-30%	71.90	72.01	71.98	72.09	72.20	72.35
λ=5%, γ=-45%	72.62	72.94	72.69	73.02	72.88	73.25
λ=5%, γ=-60%	73.46	74.12	73.51	74.19	73.68	74.40

Finally, Table 3-4 provides evidence on the relative pricing of the jump model and the augmented GBM when the discrete jumps are modelled symmetrically. In that case, the gap between the two prices becomes smaller. The maximum gap is only 0.18 (or 0.25 percent of the true option price). The reason is that the under-pricing of the positive jumps and the overpricing of the negative jumps to a large extent offset. Overall, the augmented GBM leads to a limited degree of under-pricing as the effect of the positive jumps dominates that of the negative jumps. This makes sense intuitively: negative jumps can only drive the project value down to zero, but the upward potential of the positive jumps is unlimited.

Table 3-4: Comparison of True process and GBM augmented with symmetric jump model

	Jump size σ' = 0%		Jump size σ' = 10%		Jump size σ' = 20%	
	True process	**GBM augmented**	**True process**	**GBM augmented**	**True process**	**GBM augmented**
λ=1%,γ=±15%	71.29	71.29	71.32	71.32	71.43	71.43
λ=1%,γ=±30%	71.53	71.53	71.57	71.57	71.67	71.67
λ=1%, γ=±45%	71.95	71.93	71.98	71.96	72.09	72.07
λ=1%, γ=±60%	72.52	72.47	72.56	72.50	72.66	72.60
λ=3%, γ=±15%	71.45	71.45	71.56	71.56	71.88	71.88
λ=3%, γ=±30%	72.17	72.16	72.28	72.26	72.58	72.57
λ=3%, γ=±45%	73.31	73.26	73.40	73.35	73.67	73.62
λ=3%, γ=±60%	74.76	74.62	74.84	74.70	75.08	74.94
λ=5%, γ=±15%	71.61	71.61	71.79	71.78	72.31	72.31
λ=5%, γ=±30%	72.78	72.76	72.94	72.92	73.41	73.39
λ=5%, γ=±45%	74.51	74.44	74.65	74.57	75.04	74.97
λ=5%, γ=±60%	76.55	76.37	76.66	76.47	76.98	76.79

In a second step in the analysis, I analyse the impact of initial value V_0 on the results to assess whether the fact that the option is in or out of the money makes a difference in the relative pricing of the two option models. To this purpose, I take three partial approaches. In the first approach, I fix the jump probability and mean jump size at 3 percent and 30 percent respectively. Subsequently, I use combinations of different parameter values for the jump size volatility σ_j and the initial value V_0. The jump size volatility takes values 0, 10, 20 and 30 percent while V_0 is set at 40, 80, 120, and 160 percent respectively. In the second approach, both the mean jump size and the jump size volatility are fixed at 30 percent and 10 percent respectively. The jump probability takes values of 1, 3, 5 and 7 percent, while V_0 has the same range as before. In the third approach, I keep the jump probability again fixed at 3 percent and the jump volatility at 10 percent. Now, the mean jump size varies and takes values 15, 30, 45, and 60 percent and V_0 has the same range as before.

Figure 3-1 to Figure 3-3 show the pricing effect for different values of the initial value V_0 and the jump size volatility σ. In Figure 3-1 I display the results for positive jumps, in Figure 3-2 for negative jumps and in Figure 3-3 for symmetric jumps. I have previously documented that increases in the jump size volatility increased the degree of under-pricing (overpricing) by the augmented GBM model in the case of positive (negative) shocks. Here, I observe that this under-pricing and overpricing effect gets stronger with lower – more out-of-the-money – initial project values. For the chosen parameter values, the maximum pricing gap between the true jump model and the augmented GBM is close to 0.4 percent of the true option value. Figure 3-3 shows that the overall – under-pricing – effect, which in case of symmetric shocks again is a factor less than in case of asymmetric shocks. Its maximum value is close to 0.03 percent. Although the degree of under-pricing in the case of symmetric shocks remains small, it does rise with lower initial project values.

Figure 3-4 to Figure 3-6 show the pricing effect for different values of the initial value V_0 and the jump probability λ. In Figure 3-4 the results for positive jumps are presented, in Figure 3-5 those for negative jumps and in Figure 3-6 those for symmetric jumps. The overall effects are qualitatively the same as in Figure 3-1 to Figure 3-3. There is under-pricing in the case of positive shocks (Figure 3-4) and overpricing in the case of negative shocks (Figure 3-5). The degree of overpricing and under-pricing with asymmetric shocks increases with higher jump probabilities and with lower initial project values. In the current settings, the maximum pricing gap is again close to 0.4 percent with asymmetric shocks. In case of symmetric shocks (Figure 3-6), there is structural under-pricing that increases with lower initial project values. However, the effect remains very small quantitatively.

Figure 3-1: Figure 1: Asymmetric positive jump: fixed λ=3% and γ=30%, variable V_0 (40 – 160) and jump size volatility σ* (0.0 – 0.3)

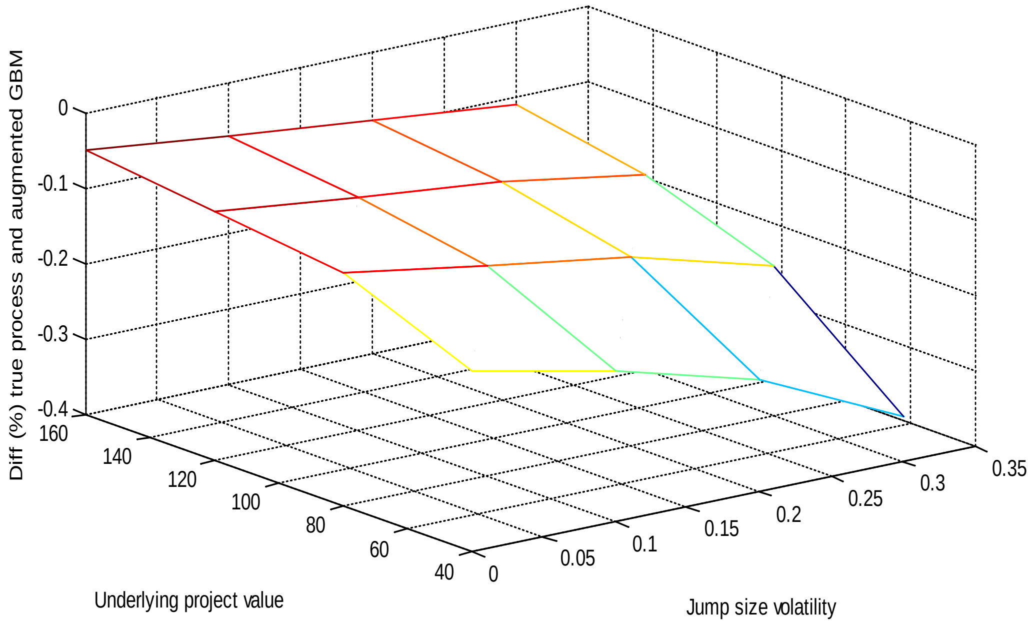


Figure 3-2: Asymmetric negative jump: fixed λ=3% and γ=30%, variable V_0 (40 – 160) and jump size volatility σ*(0.0 – 0.3)

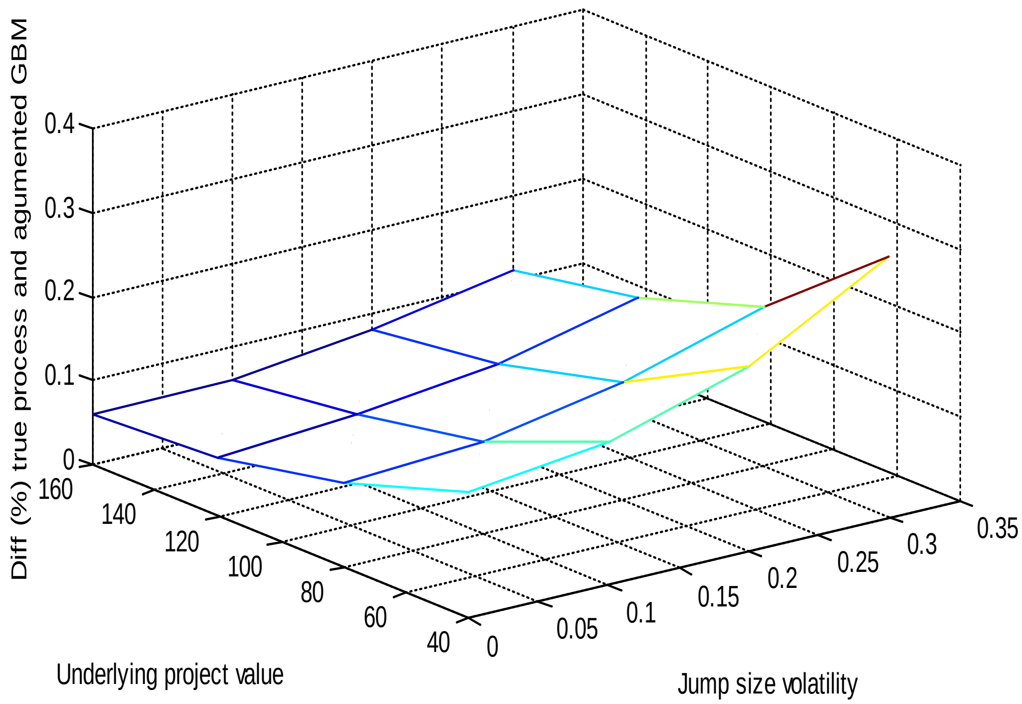


Figure 3-3: Symmetric jump: fixed λ=3% and γ=30%, variable V_0 (40 – 160) and jump size volatility σ(0.0 – 0.3)*

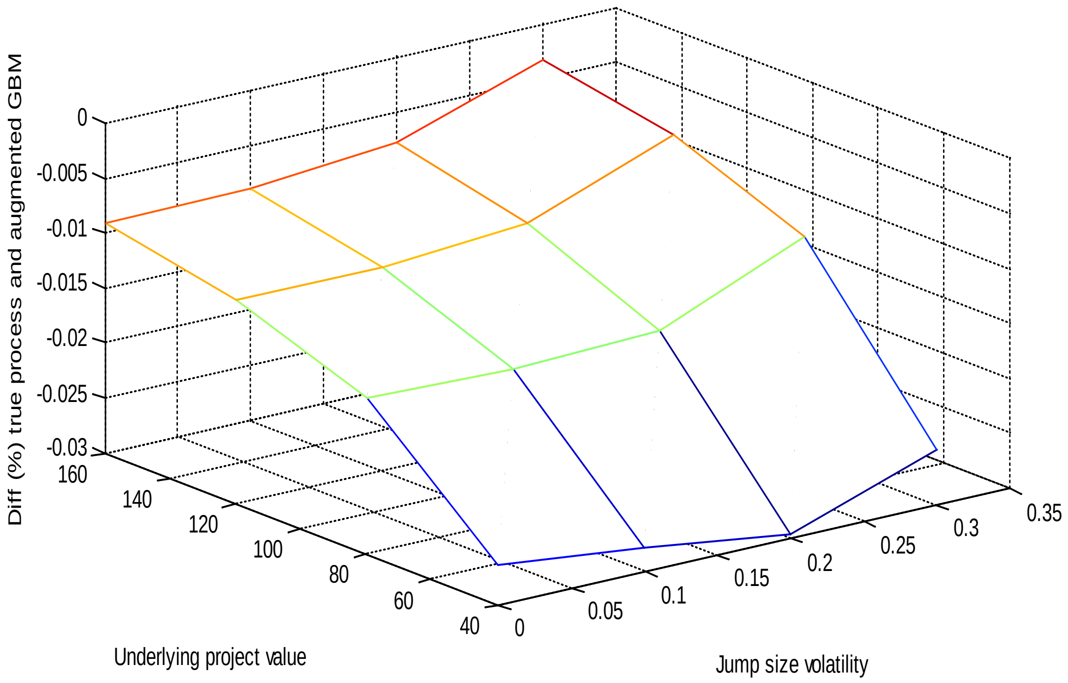


Figure 3-4: Asymmetric positive jump: fixed γ=30% and jump size volatility σ=10% variable V_0 (40 – 160) and jump probability λ (0.01 – 0.07)*

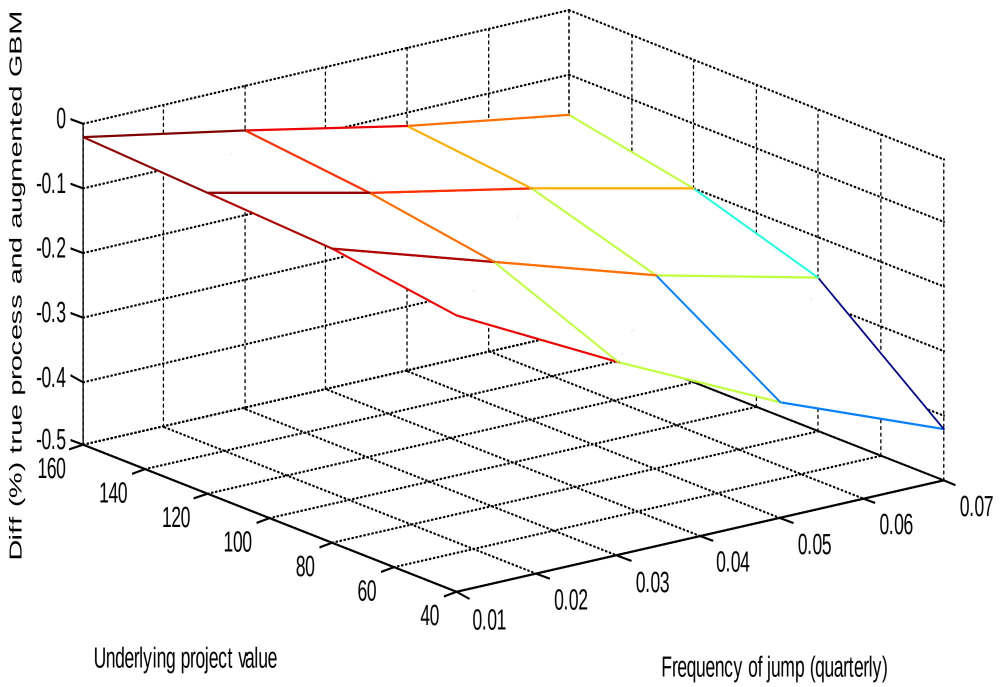


Figure 3-5: Asymmetric negative jump: fixed γ=30% and jump size volatility σ*=10% variable V_0 (40 – 160) and jump probability λ (0.01 – 0.07)

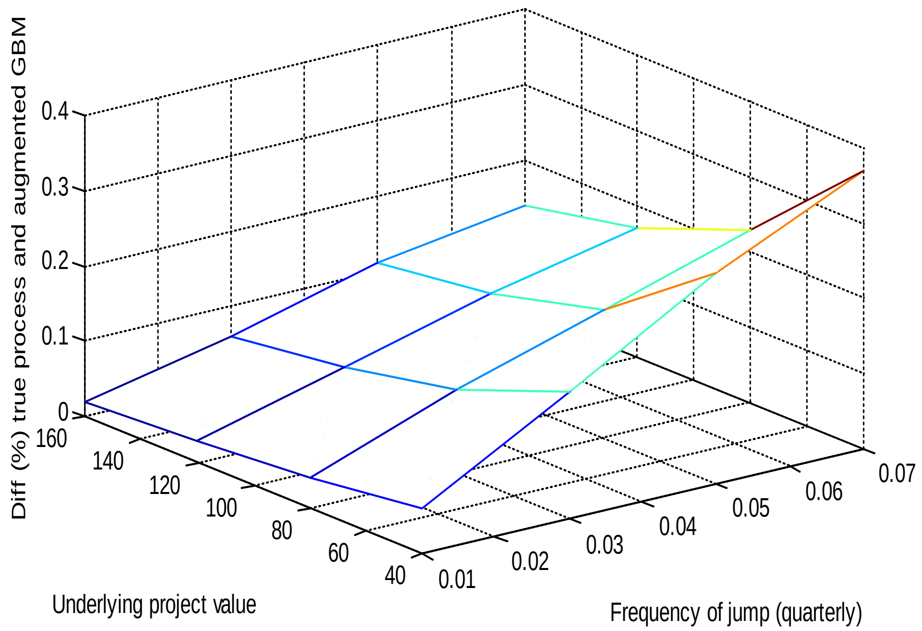


Figure 3-6: Symmetric jump: fixed γ=30% and jump size volatility σ*=10% variable V_0 (40 – 160) and jump probability λ (0.01 – 0.07)

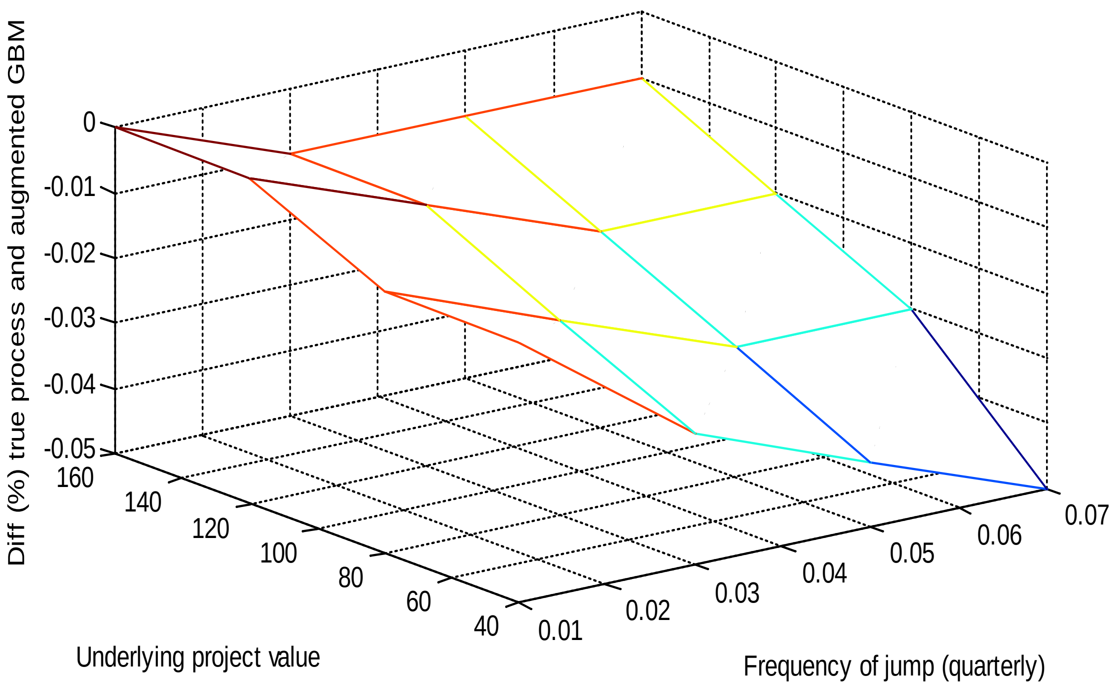


Figure 3-7: Asymmetric positive jump: fixed λ=3% and jump size volatility σ*=10%, variable V_0 (40 – 160), and jump size γ (0.15 – 0.6)

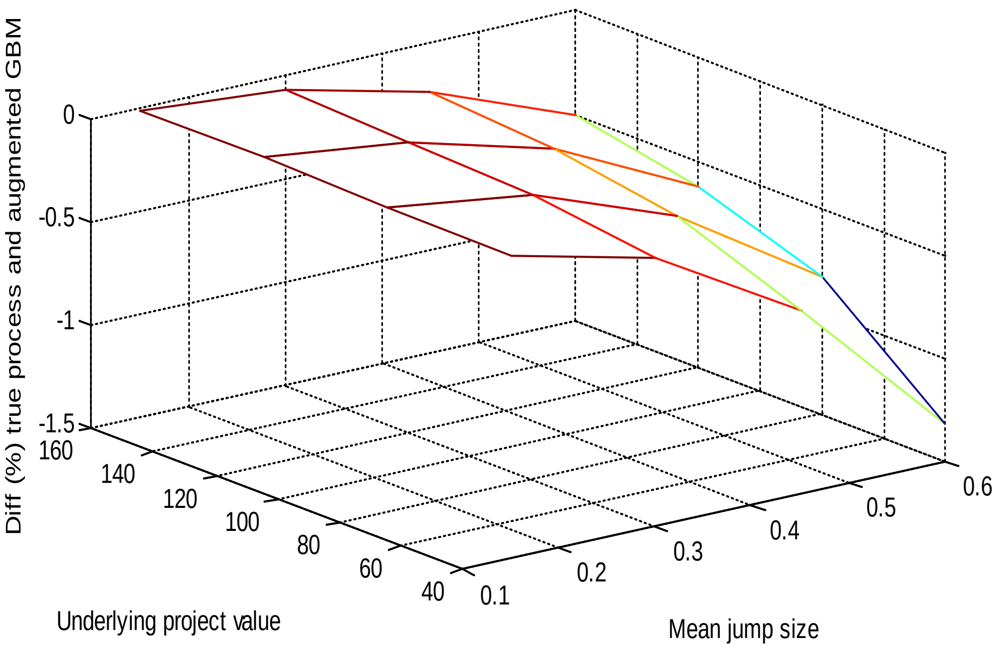


Figure 3-8: Asymmetric negative jump: fixed λ=3% and jump size volatility σ*=10%, variable V_0 (40 – 160) and jump size γ (0.15 – 0.6)

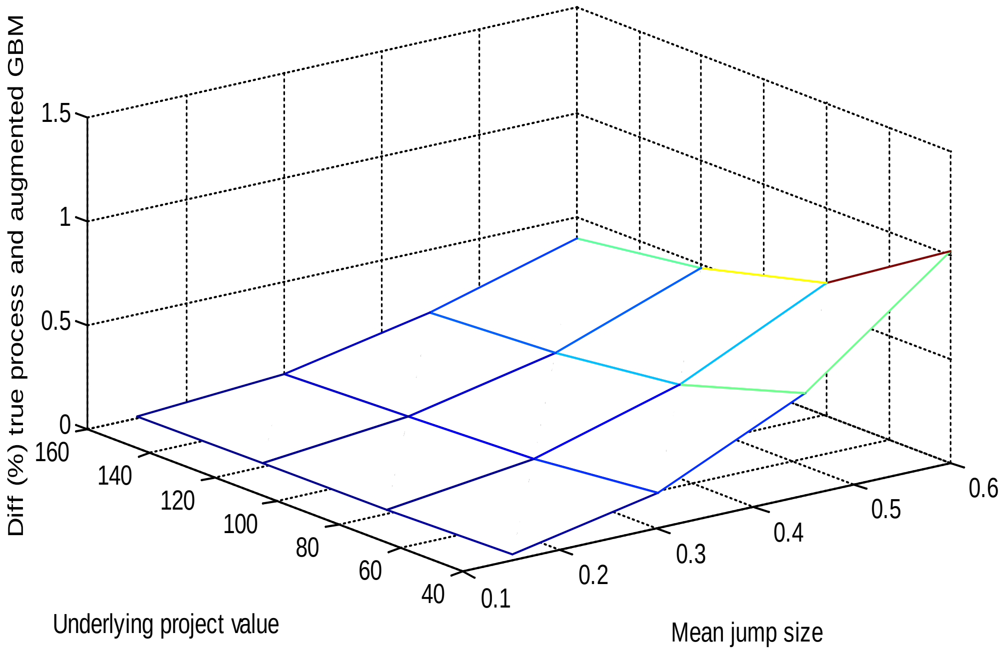


Figure 3-9: Symmetric jump: fixed λ=3% and jump size volatility σ*=10%, variable V_0 (40 – 160) and jump size γ (0.15 – 0.6)

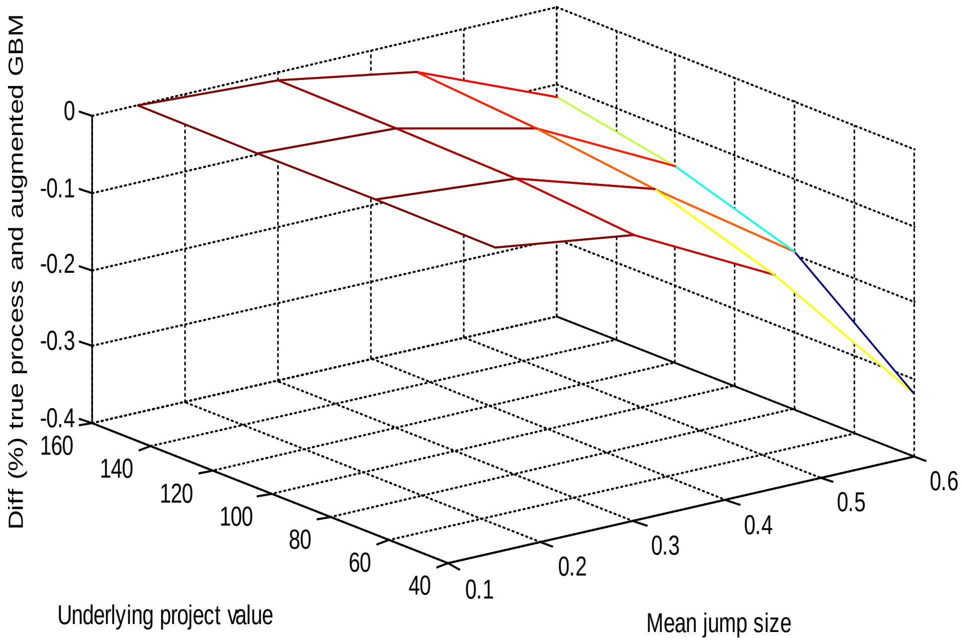


Figure 3-7 to Figure 3-9 show the pricing effect for different values of the initial value V_0 and the jump size γ. Figure 3-7presents the results for positive jumps, Figure 3-8 those for negative jumps and Figure 3-9 those for symmetric jumps. The overall effects are qualitatively the same as before, but quantitatively somewhat larger. The degree of overpricing and under-pricing with asymmetric shocks increases with higher jump probabilities and with lower initial project values. In the current settings, the maximum pricing gap is about 1.3 percent under-pricing for positive shocks and about 1 percent overpricing for negative shocks. Also in case of symmetric shocks (Figure 3-9), the overall degree of under-pricing is somewhat higher with a maximum of about 0.3 percent.

Overall, the results in section 4 suggest that approximating a jump model by an augmented GBM model leads to some overpricing in the case of negative jumps and to some under-pricing in the case of positive jumps. The pricing gap increases with jump probability, expected jump size and jump size volatility, and decreases with initial project value. For the parameter grid I have taken into consideration, the differences remain small and amount to only a few percentages of the true option value. From that perspective, the loss of using an augmented GBM model to price a real option for a project with more complex – jump – dynamics seems small. However, the true challenge is to determine the correct parameters of the augmented GBM model. For this, sufficient information is required about the precise characteristics of the underlying true stochastic process. Failure to correct for the average drift that comes from the jump process or to appropriately take into account the various sources of volatility – both jump size volatility and expected jump size – may lead to wildly deviating option prices.

3.5 Summary and conclusions

Real option modelling has become an increasingly popular approach for the valuation of large infrastructure projects as well as the valuation of innovative projects in technology-intensive industries. The choice of the appropriate stochastic process and its parameters, which drive the development of the project value, appears crucial to end up with a correct real option valuation. Theoretically, one would want to model the project´s dynamics to optimally reflect the specific character of the underlying uncertainties. In practice, the link between the type of uncertainty and the preferred valuation model seems rather loose. For the case of technical uncertainty, the literature shows that a specific type of technical uncertainty has been modelled by many different stochastic processes, and that a specific stochastic process has been used for many different types of technical uncertainty.

In this chapter, I contribute to the literature by investigating whether approximating asymmetric and symmetric jump processes by an augmented GBM leads to significant pricing errors. To this purpose, I start from a hypothetical base scenario and then perform a grid analysis across four parameter dimensions: i) jump probability, ii) mean jump size, iii) jump size volatility and iv) initial project value.

Overall, I find that the augmented GBM model under-prices (overprices) the option in case of positive (negative) jumps. It also overprices in case of symmetric jumps. The overpricing and under-pricing increase with jump probability, mean jump size, and jump size volatility and decrease with initial project value (out-of-the money options). Note that in practical applications, real options typically are out-of-the-money. Overall, the degree of overpricing and under-pricing remains limited. Especially in the case of symmetric jumps where the overpricing of the negative jumps and the under-pricing of the positive jumps to some extent offset, the resulting under-pricing is small. This suggests that using an appropriate augmented GBM model to price real options on projects with complex – jump – dynamics may not lead to significant valuation errors or incorrect investment decisions. However, the key word here is “appropriate”. Failure to correct for the average drift that comes from the jump process or to appropriately take into account the various sources of volatility – both jump size volatility and expected jump size – when specifying the augmented GBM model may result in significantly incorrect option prices.

Chapter 4
Incorporating Policy Uncertainty in a Compound Option Framework: An Application to a Hydrogen-based Transportation System in the Netherlands

4.1 Introduction

Hydrogen is an energy carrier with great potential for clean, efficient power in transport applications. With the increasing call for more sustainable energy, it has been suggested as one of the alternative transportation fuels to replace conventional fossil fuel. In light of these considerations, the European Commission has been supporting the development of hydrogen fuel cells since early 1990s with various demonstration projects such as CUTE, ZERO REGIO and HyChain Mini-Trans[23]. In the Netherlands, the Energy Agreement for sustainable Growth stipulated that by 2035 all new cars are to be zero emission vehicles. The Netherlands is working on a basis of agreements and public-private green deals; such as the “green deal for zero-emission for public bus transport in 2013”, the “green deal on zero-emission logistic vehicles” and the “green deal on hydrogen” that is being expanded in 2016.

Public investment in research, development, and demonstration has contributed substantially toward the commercial readiness of the technology. Two hydrogen refuelling stations are currently in operation in the Netherlands. The station in Rhoon (Rotterdam) is operated by Air Liquide and its hydrogen is supplied through a pipeline. The second located in Helmond is operated by WaterstofNet and the hydrogen is produced by electrolysis (60 kg/day). Three more hydrogen refuelling stations are decided for 2017; another 7 are in preparation and 5 more under investigation[24].

In spite of the advance of technology, market adoption of hydrogen as the future transportation fuel requires a comprehensive refuelling infrastructure. From production and distribution, to storage, the transition will require the establishment of a strong and reliable hydrogen fuel supply and delivery infrastructure. According to the study by Ogden et al. (1999b), it appears that customer convenience comparable to that of gasoline today requires hydrogen to be offered at 10-30% of the existing gasoline stations. The series of infrastructure investments to realize this goal will cost billions and take decades to complete. The upfront construction costs on hydrogen refuelling infrastructure will be high and could continue for a decade or more, delaying profitability until an adequate number of fuel

[23] European Commission Mobility and Transportation: //ec.europa.eu/transport/themes/urban/vehicles/road/hydrogen_en

[24] These new refuelling stations are built within the framework of regional initiatives, the TEN-T, the FCH-JU and the EIB.

cell vehicles can be produced and moved into consumer markets. Under the current cost structure, fuel cell technology cannot offer direct economic advantages to all relevant stakeholders.

Obviously, the transition from fossil fuel based energy consumption towards sustainable energy solutions is a complex societal process (Kemp et al., 2007; Meadowcroft, 2009). Making investment decisions in such a dynamic, complex environment with different sources of risk is challenging. Real option modelling has become an increasingly popular method to handle resource allocation decisions in this context (Abadie and Chamorro, 2008). As long as investors have some leeway in deferring sustainable investment decisions in the absence of any opportunity cost of waiting, real option models predict that companies will abstain from investing until more information is available or specific sources of uncertainty are resolved. This is especially the case with sustainable energy solutions, as they require high investment costs (Sanders et al., 2013). Engelen et al. (2016) showed that practitioners strongly call for governmental support, as they do not see private investors committing significant resources to such projects. Their survey on the development of a hydrogen fuel station network for cars illustrates that an overwhelming majority of the respondents agree (25%) or strongly agree (67%) with the statement about the need for significant government support of sustainable hydrogen infrastructure for investments to take-off.

Policymakers are indeed key players in creating incentives for companies to invest in sustainable energy solutions or to accelerate the development process (Blyth et al., 2007). In particular, credible long-term political commitments seem to be key drivers in inducing companies to encourage investing (Astrand and Neij, 2006). Frequent changes in investment incentives and large alterations in policy choices cause additional risk for companies instead of stimulating their commitment. In this way, companies face policy uncertainty as an additional source of risk, on top of regular market risk and technical risk (Cassimon et al., 2011b).

In this chapter, therefore, I focus on the role of policy uncertainty and apply it to an investment case of a multistage hydrogen infrastructure project. Since the project can be seen as a sequence of real options, it can be modelled as a compound option. To capture the impact of both market risk and technical risk of the project, I use the extended N-fold compound option model of Cassimon et al. (2011b). Here, market risk refers to the normal business risk the hydrogen infrastructure project incurs, such as the potential market size of hydrogen cars, the expected revenues from fuel sales, the expected cost structure, and so on. It is modelled as a Generalized Brownian Motion. Technical risk is the "exposure to loss arising from activities such as design and engineering, manufacturing, technological processes and test procedures". In other words, technical risk refers to the difficulty of realizing certain engineering features of the hydrogen project. Although some demonstration hydrogen fuelling stations exist, rolling out a large-scale network of hydrogen fuelling stations might reveal difficulties in the execution of the technical process due to untested engineering procedures. Following Cassimon et al. (2011), technical risk is modelled using discrete success–failure probabilities at each stage of the project.

This chapter contributes to the literature in three ways. First, I extend the N-fold compound option framework of Cassimon et al. (2004, 2011b) by incorporating policy uncertainty as a third source of risk. Policy risk will be modelled as a Poisson distributed jump process. I will analyse the impact on project value and/or on project decision when I incorporate policy uncertainty in the equation, next to market and technical risk. I analyse the magnitude of error in ignoring policy uncertainty as a third source of risk in compound real option models. Second, I will analyse what type of policy uncertainty has the biggest impact on the investment decision. This might give guidance to policy makers in reducing specific sources of policy uncertainty in order to stimulate investors to commit resources to sustainable energy projects. Finally, I analyse the investment case for hydrogen infrastructure investments in the Netherlands taking into account those three sources of risk.

The chapter is organized as follows. Section 2 elaborates on the different dimensions of policy uncertainty and illustrates this with investment cases. Section 3 introduces the modelling part and discusses how to incorporate policy uncertainty as a third source of risk in the N-fold compound option framework. Section 4 presents the hydrogen infrastructure investment project and analyses the impact of policy uncertainty on project value, and section 5 concludes.

4.2 Sources of Policy Uncertainty

A first source of policy uncertainty is the lack of clear and unambiguous public policy goals, which are a prime condition for private sector commitment to investments in new technologies (Zhao and Melaina, 2006). A good example is the development of wind power in Sweden. Compared to other countries such as Denmark, wind power never took off seriously in Sweden. It is generally understood that the core of the Swedish problem lies in the vague formulations of the energy policy goals for wind power (Söderholm and Pettersson, 2011). Policymakers merely announced the introduction of wind power in Sweden "without explicitly stating when and how much" (Astrand and Neij, 2006). Without a clear government strategy, private investors abstained because the ambiguous policy stance created too much uncertainty for investments. In a similar way, the impact of policy choices in the UK on the energy use in buildings is also unpredictable because it is very unclear how various choices will be put in place. Ekins and Lees (2008) gave the example of smart meters. While the British government expected in 2007 that all British homes would have smart meters within a decade, "nothing has yet been done to implement this expectation.” To induce households or energy providers to invest in smart meters, a clear and measurable policy goal is needed.

A second source of policy uncertainty is the lack of a long-term commitment in policy choices (Helm et al., 2003). This is especially true for investment decisions in the energy sector as many projects have a long investment horizon. For instance, power plants have lifetimes of about 40 years, while windmills typically have an economic horizon of 20 years. Short-term commitments that only cover part of the investment horizon signal to potential private investors a lack of political commitment (Söderholm and Pettersson, 2007). Sweden introduced green certificate trading in 2003 for stimulating wind poIr (Astrand and Neij, 2006). However, compared to a 20-year economic lifetime of a typical windmill project, the green certificate system has a much more limited time horizon (from 2003 until 2010) (Söderholm et al., 2007). The lack of long-term commitment created much uncertainty among investors whether the Swedish government had credible intentions towards wind power in the long run. Policies to reduce this source of uncertainty by extending the time horizon of the green certificate system would stimulate windmill project across Sweden (Astrand and Neij, 2006; Söderholm et al., 2007).

A third source of policy uncertainty is the lack of a supporting regulatory framework (Reinelt and Keith, 2007). A good example again is the development of wind power in Sweden. The uncertainty about the planning and permit processing procedures at the municipal level in Sweden has been a major barrier to wind power diffusion (Bergek and Jacobsson, 2010). The lack of supporting national or regional planning regimes about the siting of wind turbines thus created too much uncertainty for wind power to take off successfully in Sweden (Astrand and Neij, 2006; Wolsink, 2007). The “large differences between different municipalities in their capacity to manage wind power issues, in planning strategies, in priorities, and in motivation to support wind power” created policy uncertainty among market actors. Local planning and permit procedures Ire not compatible with national policy instruments to stimulate the diffusion of wind power inhibiting its development in SIden (Astrand and Neij, 2006).

Finally, the certainty for taking investment decisions will be enhanced by having stable policy choices. Policy choices depend on political institutions that show a preference for a certain technology at a certain moment in time (Hisschemöller et al., 2006). As political institutions change over time, so do policy choices and hence one can anticipate policy shifts. Varone and Aebischer (2001) show how the political majority and the confrontation between Democrats and Republicans in the US affect the choice of policy instruments. Two dimensions of policy stability are important: the magnitude of the policy shift and the frequency of occurrence.

The magnitude of the policy shift captures how big the change in the policy is. Policy makers' stance towards nuclear energy illustrates this. During the 1970s and 1980s nuclear energy was considered an efficient solution to growing energy demands in Europe. After the Chernobyl accident in 1986 policymakers were moving away from nuclear energy as public opinion was increasingly concerned with environmental issues (radioactive waste) and safety (risk of accidents) (Vaillancourt et al., 2008). Such policy shifts have a deep impact on investment decisions since nuclear reactors are very capital-intensive, have a long construction time and a lifetime of at least 40 years. In the 1990s many nuclear projects were cancelled and several countries moved towards gradually phasing out their nuclear energy sector. At the start of the 21st century nuclear energy returned to the policy agenda as "a cornerstone of the [energy policy] system to balance the energy mix towards non-CO_2 emitting energies." (Jean-Baptiste and Ducroux, 2003) In order to meet standards in CO_2 reduction, nuclear energy was again promoted (Verbruggen, 2008). However, the Swiss case illustrates the high level of policy uncertainty regarding investments in nuclear energy (Kannan and Turton, 2012). While the Swiss regulatory agency gave positive advice on constructing new nuclear reactors in 2010, the Swiss parliament decided to phase out nuclear energy in 2011 after the Fukushima accident. Although a reversal of this decision is still possible, this creates too much policy uncertainty for investors to commit to new nuclear projects. Bio-fuels are another example of large shifts in policy choices. Biodiesel expanded rapidly in the EU in the early 2000s due to heavy government support via tax reductions and obligations to fuel providers (Charles et al., 2007; Ng et al., 2010). However, after concerns about deforestation (Fargione et al., 2008), substitution of biomass for human consumption to fuel production (Goldemberg and Guardabassi, 2009) and rising food prices (Taylor, 2008), the EU adjusted its biodiesel policy in 2009. Some policy instruments were abandoned, while new criteria (sustainability) have been introduced. Ninni (2010) argued that the new EU policy introduced a lot of uncertainty about the future of biodiesel in the EU.

The frequency of policy changes is another important factor of policy stability. For instance, in Sweden frequent changes to wind power subsidies are considered to have hampered its development. The Swedish government introduced a 25% subsidy for wind power in 1991 and raised it to 35% in 1993. However, between 1996 and 1997 subsidies were abolished. The Swedish government reintroduced a subsidy of 15% in 1998, but terminated subsidies again in 2002 (Wang, 2006). The frequent changes increased uncertainty for investors.

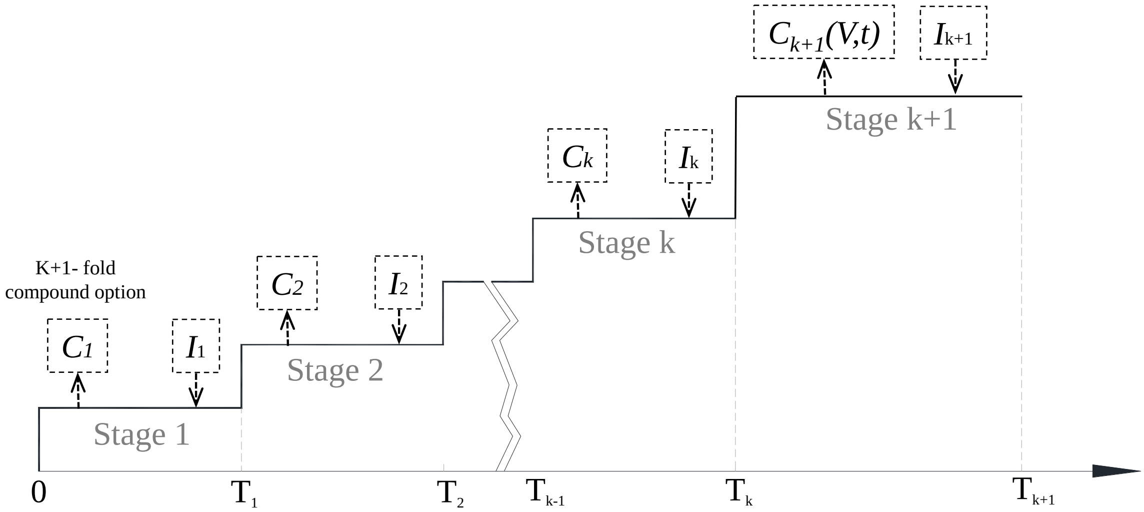
In this chapter, I focus on the stability of policy choices and examine the impact of the size of the policy change and its frequency. I apply it to investment decisions of hydrogen infrastructure for cars in the Netherlands. I explicitly assume that the policy goals for establishing a hydrogen economy are clear, that policy makers stick to a long-term framework (e.g. Hyways) and that the regulatory framework is well developed.

4.3 The Model

Compound options have been widely used in the financial literature to evaluate sequential investment opportunities. The option structure offers much more flexibility to dynamically allocate resources depending on how the sequential stages of the investment project develop over time. Large-scale capital investments are often sequential and thus require a series of irreversible investments, while significant positive project cash flows are realized only when the whole project is complete. As a typical example, the development of hydrogen infrastructure will probably start with a few fleet projects, followed by regional investments and ultimately conclude by a commercialization phase. Such an investment process may be interpreted as a sequence of options such that every investment phase creates an option for an investment in the next phase. If a previous-stage turns out to be successful, the next one will be initialized; otherwise the investment is discontinued. This process goes on until the final stage. Each stage has a certain minimum duration in which the process has to be completed for providing further information necessary for the decision of whether to invest. The whole cash in-flow of this multi-stage process is fully generated when the investment for the last stage is completed.

As illustrated in Figure 4-1, the multi-stage investment will be priced as a compound option, interpreted as a chain of call options to invest. Let us consider an investor who wants to invest on a hydrogen project whose commercial phase cannot be launched upon the successful competition of previous k investment stages. Let T_{k+1} be the time of the market launch of the hydrogen fuel, when, upon bearing the commercialization cost I_{k+1}, the firm earns the project value V. The project payoff at time T_{k+1} is $\max[V - I_{k+1}, 0]$. Let $C_{k+1}(V,t)$ denote the value at time t of this 1-fold compound option or single stage investment opportunity. I assume that the commercialization phase is reached upon investing an amount I_k, at time period T_k, with $T_{k+1} \geq T_k \geq \cdots T_2 \geq T_1 \geq 0$. The project starts with I_1 as the startup costs, while T_k and I_k are maturities of intermediate phases that lead up to the commercialization phase and the respective investment costs. At any stage k the investor can decide whether to abandon the underlying project or enter the next stage. The multi-staged investment problem may be viewed as a compound option, that is options on options, and its value may be derived in a recursive way.

Figure 4-1: An N-stage investment plan as a compound option



In the following sub-sections, I introduce the framework and present the major assumptions of the models. Our model is based on the work of Martzoukos and Trigeorgis (2002) and Cassimon et al. (2011b), and by incorporating market, technical and policy uncertainty further develops a generalized compound option valuation of hydrogen infrastructure investment.

4.3.1 Compound option model with market and technical uncertainty

Cassimon et al. (2011b) used a generalized N-fold compound option model explicitly incorporating both commercial (market) and technical uncertainty to value the development of a new drug. Here I will review their approach. As usual, the model is formulated in continuous time. Technical uncertainty refers to technical success of each investment stage by multiplying the option value at each decision point with the probability of technical success at that stage. In their valuation, the project has a commercial risk σ and technical success probabilities $p_1, p_2, \dots, p_{k+1}$ at each investment stage. The project value is unknown and is denoted by V_t at time t. It is described by a Geometric Brownian motion:

$$dV_t = \mu V_t dt + \sigma V_t dW_t, \qquad [4\text{-}1]$$

where μ and σ represent the growth rate and the standard deviation of the project value. The stochastic variable dW_t follows a Wiener Process with $dW_t \sim N(0, \sqrt{dt})$.

I define a sequence of call options with value C_k on the call option whose value is C_{k+1} with exercise price I_k and expiry date T_k, such that

$$C_k(C_{k+1}(V,T_k),T_k) = p_k max[C_{k+1}(V,T_k) - I_k, 0], \qquad [4\text{-}2]$$

where $C_{k+1}(V,T_k)$ stands for the value of the underlying compound option. The pricing formula for the $k+1$-fold compound option, $C_1(V,0)$ at $t=0$, is given by the following expression:

$$C_1(V,0) = h_{k+1} V N_N\big(a_1, a_2, \dots, a_N;\ R_1^{k+1}\big) - \sum_{l=2}^{k+1} h_l!\, I_l e^{-rT_l} N_l\big(b_1, b_2, \dots, b_l;\ R_1^l\big) + \\ -h_1 I_1 e^{-rT_1} N_1(b_1), \qquad [4\text{-}3]$$

where

$a_l = b_l + \sigma\sqrt{T_l};\quad l = 2, \dots, k+1$ and

$b_l = \frac{ln\frac{V}{V_l^*} + (r - \frac{\sigma^2}{2})T_l}{\sigma\sqrt{T_l}};\quad l = 2, \dots, k+1.$

V_l^* is the at-the-money option solution of

$$C_{l+1}(V, t_l) = I_l;\quad l = 1, \dots, k+1 \qquad [4\text{-}4]$$

$$\rho_{fg} = \sqrt{\frac{T_f}{T_g}};\quad 1 < f < g \le k+1 \qquad [4\text{-}5]$$

$$R_1^l = (a_{fg}^l)_{f,g=1,2,\dots,l}\ with\ \begin{cases} a_{ff} = 1 \\ a_{fg} = a_{gf} = \rho_{fg} \end{cases};\ 1 < f < g \le k+1 \qquad [4\text{-}6]$$

and

$h_{k+1} = p_1 p_2 \dots p_k\, p_{k+1}$

$$h_k = p_1 p_2 \dots p_k \qquad [4\text{-}7]$$

$h_2 = p_1 p_2$

$h_1 = p_1.$

For details of the proof I refer to the original paper by Cassimon et al. (2011).

4.3.2 Incorporating policy uncertainty in the compound option model

Policy measures, e.g. in terms of subsidies, taxation schemes or regulatory requirements, can play a key role when it comes to vehicle and fuel price. Vehicle and fuel price together with road and excise taxes define the break-even point of different types of fuels. Under the current cost structure, fuel cell technology cannot offer economic advantages to all relevant stakeholders. Government strategies and corresponding policy measures are able to create an environment that either encourages or discourages the use of the sustainable technology through fiscal and non-fiscal measures. The arrival of new information concerning such policy risk often occurs as various discrete events. Examples of different event classes might be political support (positive jumps), subsidy withdrawals (negative jumps), or constant changes in new regulatory or environmental decisions (positive and negative jumps).

Jumps are typically described by a Poisson process, a process subject to jumps of fixed or random size for which the arrival times follow a Poisson distribution. The Poisson distribution is a convenient tool when one counts the number of events across time or space. Formally denoted by $\{X_t\}_{0\le t<\infty}$ it is a counting process that can be interpreted as the number of events occurring during a particular time interval, e.g. number of defaults, etc. The increments of $\{X_t\}$ are independent. At time $t = 0$, I have $X_0 = 0$. The probability of x events $(x \ge 0)$ in the time interval $[t, t + 1]$ is given by the Poisson distribution: $P[X_{t+1} - X_t = x] = \frac{e^{-\lambda t}(\lambda t)^x}{x!}$. I infer that the Poisson probability is stationary, as it does not depend on the time shift. Jumps are assumed to be independent; they can arrive Poisson-distributed in time with λ measuring the frequency of the jumps that indicates the average number of events in the given time interval.

I assume that the effect of market uncertainties on the project value is likely to evolve as a continuous process, while the emergence of government policy will change the project value in a discrete contingency. The project value $\bar{V}_t$ follows the dynamics of a combination of a Geometric Brownian Motion and a Poisson jump process:

$$\frac{d\bar{V}_t}{\bar{V}_t} = \bar{\mu}\, dt + \sigma dW_t + \sum_{j=1}^{J} (\gamma_j - 1) dq_j. \qquad [4\text{-}8]$$

Equation [4-8] shows that the underlying project value $\bar{V}$ has an instantaneous expected return $\bar{\mu}$ and is driven by the Wiener process W_t with mean zero and an instantaneous standard deviation σ. Note that the actual trend of the process $\bar{V}_t$ not only includes the risk neutral drift composed of a risk-free interest rate r adjusted with some form of convenience yield δ, but also includes a jump compensator resulting in the following expression $\bar{\mu} = r - \delta - \sum_{j=1}^{J} \lambda_j E[\gamma_j - 1]$. Moreover, in this general specification there are J different sources of rare events (jumps). The jump process j experiences a jump of size $\gamma_j - 1$ (i.e. the project value jumps from $\bar{V}_t$ to $\gamma_j \bar{V}_t$) when the jump counter dq_j equals 1, which happens with probability λ_j. Otherwise, dq_j equals 0. It is assumed that the stochastic shocks

dW_t and dq_j are independent. Furthermore, I assume γ_j to be log-normally distributed with $\ln\gamma_j \sim N(\beta_j, \sigma_j{}^2)$, and $N(.)$ denoting a normal density function with mean β_j and variance $\sigma_j{}^2$. I will refer to β_j as the log jump size from now on and note that $E[\gamma_j] = \exp\left(\beta_j + \frac{1}{2}\sigma_j{}^2\right)$. From above, it follows that each jump process j, with $j = 1, \dots, J$ can be characterized by three parameters: the arrival probability λ_j, the mean log jump size β_j and the logarithmic jump size standard deviation σ_j.

In order to determine the value of the investment opportunity $\bar{C}_k(\bar{C}_{k+1}(\bar{V}, T_k), T_k)$ at each stage T_k, I need to find the boundary condition iteratively:

$$\bar{C}_k(\bar{C}_{k+1}(\bar{V}, T_k), T_k) = p_k max[\bar{C}_{k+1}(\bar{V}, T_k) - I_k, 0]. \qquad [4\text{-}9]$$

Equation [4-9] leads to

$$\bar{C}_k(\bar{C}_{k+1}(\bar{V}, T_k), T_k) = \begin{cases} p_k[\bar{C}_{k+1}(\bar{V}, T_k) - I_k], & if\ \bar{V}_{T_k} \geq \bar{V}_k^* \\ 0, & if\ \bar{V}_{T_k} < \bar{V}_k^* \end{cases}, \qquad [4\text{-}10]$$

where $\bar{V}_k^*$ is the value of underlying option at the money at time T_k. If the value of $\bar{V}_t$ at time $t = T_k$ is greater than the threshold $\bar{V}_k^*$, the investment continues to the next stage, otherwise the project will be abandoned. Let $s_{k+1} = \sum_{i=1}^{k+1} n_i$ be the total number of jumps in the interval $[0, T_{k+1}]$, with $T_1 \leq T_2 \leq \dots \leq T_{k+1}$, and let $\tau_{k+1} = T_{k+1} - T_k$ be the time interval between consecutive time points. I can make a decomposition of that sum of jumps across the J sources of risk. Denoting by n_{i_j} the number of jumps of the jump risk process j in the time interval τ_i from the identity $n_i = n_{i_1} + n_{i_2} + \dots + n_{i_J}$, I get $s_i = \sum_{i=1}^{i} \sum_{j=1}^{J} n_{i_j} = \sum_{j=1}^{J} \sum_{i=1}^{i} n_{i_j} = \sum_{j=1}^{J} s_{i_j}$ with s_{i_j} being the number of jumps of the jump risk process j in the time interval T_i. After s_i jumps, the total standard deviation of the project value is given by the sum of the standard deviations of the Geometric Brownian Motion and the Poisson process respectively:

$$\sigma_{s_i}^2 = \sigma^2 + \frac{\sigma_{\gamma_i}^2}{T_i}, \qquad [4\text{-}11]$$

where

$$\sigma_{\gamma_i}^2 = \sum_{p=1}^{i} \sum_{j=1}^{J} n_{p_j} \sigma_j^2 = \sum_{j=1}^{J} \sigma_j^2 s_{i_j}$$

When the project value follows a jump-diffusion process as Equation [4-8], then the expected present value of the $k+1$-staged investment project with final pay-off equal to $\max[V-I_{k+1},0]$ and with corresponding investment costs $(I_1, I_2, \dots, I_{k+1})$ at time line $(T_1, T_2, \dots, T_{k+1})$ is:

$$\bar{C}_1(\bar{V},0) =$$
$$h_{k+1}\prod_{p=1}^{k+1}\{\sum_{n_{p_1},n_{p_2},\dots,n_{p_J}=0}^{\infty}\prod_{j=1}^{J}[\frac{e^{-\lambda_j\tau_p}(\lambda_j\tau_p)^{n_{p_j}}}{n_{p_j}!}]\,\bar{V}(0)\,exp(-\delta_{s_{k+1}}T_{k+1})\,N_{k+1}(\bar{a}_{s_1},\bar{a}_{s_2},\dots,\bar{a}_{s_{k+1}};\,\Xi_{k+1}\,)\}-$$

$$-\sum_{i=1}^{k+1}\{h_i I_i\prod_{p=1}^{i}[\sum_{n_{p_1},n_{p_2},\dots,n_{p_J}=0}^{\infty}\prod_{j=1}^{J}[\frac{e^{-\lambda_j\tau_p}(\lambda_j\tau_p)^{n_{p_j}}}{n_{p_j}!}]\,e^{-rT_i}N_i(\bar{b}_{s_1},\bar{b}_{s_2},\dots,\bar{b}_{s_i};\,\Xi_i)]\}, \qquad [4\text{-}12]$$

where

$$\delta_{s_p} = -\frac{\beta_{\gamma_p}+\frac{1}{2}\sigma_{\gamma_p}^2}{T_p}+\delta+\sum_{j=1}^{J}\lambda_j\left(\exp\left(\beta_j+\frac{1}{2}\sigma_j^2\right)-1\right)=$$
$$=-\frac{\beta_{\gamma_p}+\frac{1}{2}\sigma_{\gamma_p}^2}{T_p}+\delta+\sum_{j=1}^{J}\lambda_j\left(\exp\left(\beta_j+\frac{1}{2}\sigma_j^2\right)-1\right),$$

$$\bar{a}_{s_p} = \bar{b}_{s_p}+\sigma_{s_p}\sqrt{T_p};\;\; \bar{b}_{s_p} = \frac{ln\frac{\bar{V}}{\bar{V}_p^*}+\left(r-\delta_{s_p}-\frac{1}{2}\sigma_{s_p}^2\right)T_p}{\sigma_{s_p}\sqrt{T_p}}, \text{ p=1,…,i},$$

$$\sigma_{s_p}^2 = \sigma^2+\frac{\sigma_{\gamma_p}^2}{T_p}, \text{ p=1,…,i},$$

$$\beta_{\gamma_p} = \sum_{r=1}^{p}\sum_{j=1}^{J}n_{r_j}\beta_j = \sum_{j=1}^{J}\beta_j s_{p_j}, \text{ p=1,…,i, and}$$

$$\sigma_{\gamma_p}^2 = \sum_{r=1}^{p}\sum_{j=1}^{J}n_{r_j}\sigma_j^2=\sum_{j=1}^{J}\sigma_j^2 s_{p_j}, \text{ p=1,…,i.}$$

Here Ξ_{k+1} denotes a $k+1$-dimensional symmetric correlation matrix with elements

$$\rho_{s_f s_g} = \frac{\sigma_{s_f}\sqrt{T_f}}{\sigma_{s_g}\sqrt{T_g}}\;, with\;\; 1\le f<g\le k+1.$$

Proof. See Appendix B, based on Andergassen and Sereno (2012).

4.4 HyWays Case Study

This section applies our compound option model to the case of hydrogen refuelling infrastructure investment in the Netherlands. First, I provide some background information on the HyWays case study, the input parameters and the assumptions that will be used in the computations. Next, I will move to our empirical experiment of policy uncertainty as a third source of risk, then to market and technical uncertainty. Policy uncertainty will be modelled as a jump process with two driving forces: the magnitude of the policy shift and its frequency of occurrence.

4.4.1 Description of the hydrogen infrastructure project

The hydrogen infrastructure project involves establishing a fuel station network in the Netherlands. I largely follow the roadmap as set forward by the HyWays project in the EU. This project laid out a phased roadmap for hydrogen stations in 10 European countries (Finland, France, Germany, Greece, Italy, the Netherlands, Norway, Poland, Spain, and the United Kingdom) (HyWays, 2007). This hydrogen energy roadmap assumes three phases. Phase I is the pre-commercial phase and assumes 10,000 hydrogen vehicles on European roads. Phase II is the early commercialization phase and assumes up to 500,000 hydrogen cars in the 10 participating countries. Finally, phase III is the full commercialization phase and assumes increasing hydrogen user numbers (from a first step of 500,000 over a second step of 4 million to a third step of 16 million hydrogen cars). Since all numbers are for the total users in the 10 participating countries, I need to scale those numbers to obtain estimates for the Dutch market. When measured in terms of the number of users, the Netherlands account for 3.34% of the total target population in the EU, while they account for 3.95% of the kilometres of roads in the EU (Stiller et al., 2008). Accordingly, I scale the expectations of the number of future hydrogen users in HyWays with a factor of 3.50%, which corresponds to a maximum of 640,000 hydrogen cars over 34 years by the end of phase III.

The time path of the adoption of hydrogen fuelled cars can be expected to depend on the availability of an appropriate infrastructure in the form of a network of refuelling stations. As a consequence, the speed of construction of these stations is an important parameter in the analysis. I base our choice of construction speed on the HyWays case. It assumes a slow start with only 100 stations built in the first 14 years. After that, investment increases significantly with the building of an additional 35 stations each year for the next 20 years, until 2044.[25] I will use Li et al.'s "Conservative" scenario in this study. In the following subsections, I will demonstrate how the model is applied in strategic decision making with the HyWays example.

4.4.2 Input parameters and assumptions

The next step is to compute the corresponding operating cash flows for each project phase, where profits come from the differences between hydrogen retail revenue and production cost. This requires a number of assumptions with respect to the input values of all parameters of the cash flow model, including hydrogen demand for fuel cell passenger vehicles, consumption of hydrogen per vehicle,

[25] Li et al. (2016) designed six different scenarios with respect to the build-up of refuelling stations and the corresponding market penetration of hydrogen fuel cell vehicles over the three phases between 2010 and 2044. The building speed assumed in this paper corresponds to their "Conservative" scenario.

retail price and production cost of hydrogen, etc. I assume that each vehicle will use approximately 0,7 kg of hydrogen each day, amounting to 255,5 kg per year. For an average fuel cell vehicle with a fuel economy of 80 to 96 kilometres per kg, this would accommodate about 56 to 64 kilometres of driving on an average day (Ogden, 1999a; CaFCP, 2008). The retail price of hydrogen is estimated to be about €4/kg. Although hydrogen is much cheaper produced from natural gas, the production process is always associated with the emission of greenhouse gases and local pollutants (Haryanto et al., 2005). Sustainable hydrogen cost is assumed to be about €5/kg (phase I), but due to technical learning, it will gradually decrease to €4/kg in phase II and a long-term production cost of €3,4/kg in phase III (adapted from Lebutsch and Ieda, 2011 and Benthem et al., 2006). This includes all the relevant expenses, for instance, transportation to the refilling station and carbon capture and storage (CCS) costs if necessary.

After 2044, annual operational cash flows are assumed to remain constant forever. Their present value in 2044 is used in the computations as the residual value of the investment. For the computations, I furthermore use a 25.5% marginal tax rate (KPMG, 2011), an average Eurozone inflation rate of 2.24% (ECB, 2011), a 21.21% net working capital requirement in a given year (as percentage of the sales) (Damodaran, 2011), and a straight-line depreciation over the 20 year economic life of each station. I further assume the risk-free interest rate $r = 1.13\%$ and convenience yield $\delta = 0.3\%$. The cost of a hydrogen fuel station depends upon many factors, including the type of station, location, equipment manufacturing volume and continuing technology advancements. Here, I base our assumptions on Lebutsch and Weeda (2011). I assume a standard hydrogen station initially costs €0,95 million. Unit investment costs will decrease over time as a result of economies of scale and learning. To reflect this, I specify the cost function $\omega(N) = \alpha \cdot N^{-b}$, where $\omega(N)$ is the investment cost of the Nth unit, b is a learning parameter ($b = -0.0465$) and α the investment cost of the first unit (€0,95 million). Investment every year is determined based on the number of stations to be built.

4.4.3 Base case valuation

The deployment of hydrogen refuelling stations is a significant market barrier to the successful introduction of fuel cell vehicles. The risk structure is a key element in determining how high returns must be to enable investment into renewables. An improved understanding of the costs and financial risks associated with deploying hydrogen stations can help to reduce this market barrier. In our approach, the investment decision is affected by factors influencing the cash flows of the project. The main factors deciding the annual cash flows are revenues, the operational and maintenance costs, and tax. By calculating the discounted cash flows I can decide whether the investment in a specific investment phase is profitable. Investment costs will be estimated based on the number of refuelling stations to be built. Revenues will be generated through the retail sales of hydrogen fuel required to support fuel cell vehicles on the road. Furthermore, these values in turn serve as input for the computation of the time path of cash flows for each investment phase as well as the real option value at the start of the project. Uncertainty with respect to any of the factors affecting the cash flows can be translated into investment risk by using a real option approach. On this basis, I can decide whether the investment should be undertaken immediately or be postponed.

Under the assumptions made, investors will only obtain profits from around year 2028 at phase III as the cash flows generated from the fuel stations in the pre- and early-commercialization phase are negative. The underlying project value V is derived from the present value of the net cash flows at full commercialization during phase III and is equal to €268.4 mln. The exercise price $I_3 = €520.1$ million is the corresponding investment on refuelling stations at phase III. During the earlier two stages the net investment costs are estimated from the cost of building stations minus any incoming cash flows from selling hydrogen fuel. For phase II this amounts to $I_2 = €105.1$ million. Similarly, for phase I I obtain $I_1 = €37.1$ million. This is the sum of all the negative cash flows investors need to undertake, together with the upfront investments of 30 stations.

To get a first view on the role of the different uncertainties, I start with computing the project value using the N-fold compound option model under the assumption that only market uncertainty is present. Subsequently, I add technical uncertainty. The results are in Table 4-1. When only market uncertainty is taken into account with volatility parameter $\sigma = 66.75\%$, the three-phase hydrogen infrastructure project has an option value of €87.4 million. Accounting for today's up-front investment of €37.1 million, this provides a total project value of €50.3 million. In a second step, I incorporate technical risk in the option price model as developed in section 3.1. I assume there is an 80% likelihood that the investors will actually enter the final commercialization stage upon success of the early-commercialization, which itself has a 70% success probability. Therefore, the conditional probability at the start of the project of ultimately moving to full commercialization equals 56%, which is the cumulative success probability of the previous two stages. Taking this into account reduces both the option value and the project value significantly. The option value falls to €38.1 million, the project value to €1.0 million. Obviously, the initial investment costs are not affected. Overall, the positive project value still leads to an investment decision according to the real option framework.

Table 4-1: The benchmark compound option and project value (in € mln)

Market Uncertainty			**Market + Technical Uncertainty**		
Option Value	Project Value	Investment Decision	Option Value	Project Value	Investment Decision
87.4	50.2	Invest	38.1	1.0	Invest

4.4.4 Incorporating policy uncertainty

Addressing environmental impacts has long been an objective of energy policy in many countries. However, actual policy has generally been unclear, unambiguous and not guaranteed. In addition to technical uncertainty, investors are also facing policy uncertainty. The type of policy and the degree of intervention can vary significantly from one country to another and appears to be largely influenced by the awareness of and the perceived severity of the problem in question. Examples are the introduction (positive), withdrawal (negative) or modification (ambiguous) of specific subsidies or tax facilities and changes in regulatory and procedural restrictions (ambiguous). Nevertheless, investors are mostly interested in minimizing risks of costs and of revenue disruption. One of their biggest fears seems to be the continuity of energy policy; therefore, climate policy uncertainty is often considered to play a negative role on private-sector investments. Some research even argues that policy uncertainty raises risk premium and lead investors to delay spending and investment until this uncertainty has been resolved.

In practice, policy changes are relatively infrequent – in comparison with general financial market information – and arrive at discrete moments in time. Here, I model policy uncertainty with Poisson jump processes embedded in a sequential N-fold compound option. As described in Section 3.2, policy uncertainty may arise from different sources. Here I abstract from these underlying sources and focus on the size and frequency of policy changes to assess their impact on the hydrogen project value. A policy event (jump) class of type i is modelled with the frequency λ_j of (Poisson-distributed) jump arrivals with mean jump size β_j and standard deviation of jump size σ_j. The parameter λ_j represents the frequency of discrete policy changes. That is, it gives an indication of the long-term consistency of public policy. Parameter β_j represents the average size or impact of a government intervention. As argued before, policy may, for example, display structural changes in direction with enormous impact as well as marginally change regulatory or fiscal instrument settings with much less of an impact. σ_j is the standard deviation of the size of the policy event and measures the uncertainty of the size of the jump, that is, the size of the impact a policy change will have on the project value.

To investigate the impact of policy uncertainty on the project value of the hydrogen infrastructure investment, I design a simple experiment in which a variation of jump processes is considered. Apart from the jump process, I use the base case specification that, as presented in Table 4-1, leads to a project value of €1 million in the absence of policy uncertainty. Remember that jumps represent policy changes. I focus on variations in the average size β_j and frequency λ_j of jumps. In addition, I distinguish between cases where policy shocks are symmetric and asymmetric. With symmetric jumps, policy shocks that increase the project value are equally likely as shocks that decrease the project value. With asymmetric jumps, I assume negative shocks dominate. Across all variations, I keep the uncertainty σ_j about the size (impact) of the shock fixed at 0.1.

4.4.4.1 Symmetric positive and negative policy shocks

First, I consider the case of symmetric shocks. The probability of a jump occurring in Δt time equals λ_j, and I choose λ_j to be in the range from 0.05 to 0.5. In our example, I take the period Δt to be one quarter. When λ_j equals 0.05, the probability of 1 jump in every quarter is 5 percent, that is, I expect 1 jump every 5 years. On the other extreme, when λ_j equals 0.5 the probability in any period is 50 percent and I expect a jump every six months. The impact of a policy change on the project value is measured by the size of the jump as a percentage of the initial project value. I consider variations in the expected size of the jump β_j from 0.1 to 0.5, with steps of 0.1. That is, β_j can be ± 0.1, ± 0.2, ± 0.3, ± 0.4 and ± 0.5. For example, if β_j equal +0.2, the expected impact of a policy change on the project value – once it occurs – is an increase of 20 percent, and if β_j equals -0.2, the expected impact of a policy change on the project value is a decrease of 20 percent. In addition, I assume uncertainty about the actual impact of the jump, reflected in the fact that σ_j is 0.1. It implies that if a policy change (jump) occurs and the relevant jump distribution has a β_j equal to +0.2, the actual impact can – with small probability – be close to zero as well as close to +0.4 (forty percent).

Table 4-2: Project value with symmetric jumps (in € mln)

λ_j	$\beta_j = \pm 0.1$ $\sigma_j = 0.1$	$\beta_j = \pm 0.2$ $\sigma_j = 0.1$	$\beta_j = \pm 0.3$ $\sigma_j = 0.1$	$\beta_j = \pm 0.4$ $\sigma_j = 0.1$	$\beta_j = \pm 0.5$ $\sigma_j = 0.1$
0.05	1.7	2.7	3.9	5.7	7.8
0.1	2.5	4.4	7.0	10.5	15.1
0.2	4.0	7.9	13.4	20.8	30.7
0.3	5.5	11.6	20.1	31.9	47.9
0.4	7.1	15.3	27.2	43.9	66.8
0.5	8.7	19.2	34.7	56.7	87.6

Table 4-2 shows the results. Compared to the base case that has a total project value of €1 million, adding policy uncertainty unambiguously increases the option value of the project. The upper left cell where the probability of a policy event is 5 percent and the expected size of the impact ± 10 percent, shows a project value equal to €1.7 million. Increasing λ_j to 50 percent while keeping β_j fixed at ± 10 percent, raises the project value to €8.7 million. Keeping λ_j and σ_j constant while increasing β_j to ± 50 percent results in a roughly comparable increase in project value to €7.8 million. Increasing both the frequency and the expected impact to their maximum value causes the project value to increase to €87.6 million, as shown in the lower right cell of Table 4-2. Obviously, the two effects reinforce one another in a non-linear way. The unambiguous rise of the project value with the introduction of symmetric policy shocks can be easily explained. Additional jumps increase the overall variance of the project. Moreover, the higher the expected size of the jump and the higher the variation around the average value, the more probability mass is reallocated towards the tails of the distribution of the underlying asset's return. Due to the asymmetry of the option contract, a higher probability of extreme positive shocks increases the prospect for higher positive returns, which increases the value of a call option, where a higher prospect of extreme negative shocks affects the call option value much less.

4.4.4.2 Asymmetric positive and negative policy shocks

Next, I focus on a case where negative and positive policy shocks still occur but with different probabilities. This corresponds to a situation where policy is constantly changing especially negatively due to events such as political instability, legal security and administrative hurdles etc.

Technically, I assume that the probability of positive policy shock λ_+ equals 5 percent, and the probability of negative policy shocks λ_- increases from 5 percent to a maximum of 50 percent. The range of values for the expected size of the policy shocks is the same as in the case of symmetric shocks. That is, β_j can be ±0.1, ±0.2, ±0.3, ±0.4 and ±0.5. The results are shown in Table 4-3.

Table 4-3: Project value with asymmetric jump probability (in € mln)

λ_+	λ_-	$\beta_j = \pm 0.1$ $\sigma_j = 0.1$	$\beta_j = \pm 0.2$ $\sigma_j = 0.1$	$\beta_j = \pm 0.3$ $\sigma_j = 0.1$	$\beta_j = \pm 0.4$ $\sigma_j = 0.1$	$\beta_j = \pm 0.5$ $\sigma_j = 0.1$
0.05	0.05	1.7	2.7	3.9	5.7	7.8
0.05	0.1	0.6	0.4	0.3	0.4	0.5
0.05	0.2	-0.1	-0.8	-1.0	-0.8	-0.4
0.05	0.3	-0.8	-1.9	-2.3	-2.0	-1.4
0.05	0.4	-1.4	-3.0	-3.5	-3.3	-2.5
0.05	0.5	-2.1	-4.1	-4.8	-4.5	-3.6

Note that the first rows of Table 4-2 and Table 4-3 coincide with $\lambda_+ = \lambda_- = 0.05$. Keeping the probability of positive jumps fixed $\lambda_+ = 0.05$, I further increase the probability of negative jumps λ_-. With the divergence of the two probabilities, the project value starts to decrease and quickly becomes negative. Because of the higher chance of negative shocks, the option is more likely to become significantly out-of-the-money, requiring more subsequent positive shocks to be exercised. As a result, the project becomes less attractive for investors. Table 4-3 indicates that it is optimal to invest only when $\lambda_+ = 0.05$ and $\lambda_- < 0.2$. If the probability of negative policy surprises gets too large, investors will refrain from investing.

A second point to mention is that the project value in Table 4-3 does not develop monotonically with increasing expected jump size β_j. For instance, when λ_- equals 0.3, the project value first declines from -0.8 to -2.3 when β_j increases from ±10 percent to ±30 percent. However, when β_j increases further, the project value starts rising again. The reason for this is that the small possibility of a positive shock becomes more important for the project value when the expected size of the shock – when it occurs – increases sufficiently. In that case, the small probability of an extremely large shock may be enough to bring the option into the money again.

4.4.4.3 Negative policy shocks only

Finally, I turn to the situation where policy changes only have negative effects. Similar to the case of symmetric shocks, I assume the jump frequency λ_j to be in the range from 5 to 50 percent per period and the expected size of the jump to vary from 10 to 50 percent. However, now only negative expected jump sizes are considered, that is, $\beta_j \in [-0.1, -0.5]$.

Table 4-4 shows that in most situations negative project values emerge, making investment an unattractive option. When either policy shocks with a negative impact become more frequent or the expected impact gets too large, the optimal decision is not to invest.

Table 4-4: Project value with negative jumps (in € mln)

$\boldsymbol{\lambda_j}$	$\boldsymbol{\beta_j = -0.1}$ $\boldsymbol{\sigma_j = 0.1}$	$\boldsymbol{\beta_j = -0.2}$ $\boldsymbol{\sigma_j = 0.1}$	$\boldsymbol{\beta_j = -0.3}$ $\boldsymbol{\sigma_j = 0.1}$	$\boldsymbol{\beta_j = -0.4}$ $\boldsymbol{\sigma_j = 0.1}$	$\boldsymbol{\beta_j = -0.5}$ $\boldsymbol{\sigma_j = 0.1}$
0.05	0.6	0.4	0.3	0.1	0.1
0.1	0.3	-0.2	-0.3	-0.9	-1.4
0.2	-0.4	-1.3	-1.6	-1.9	-2.7
0.3	-1.1	-2.5	-2.9	-3.0	-3.9
0.4	-1.8	-3.6	-4.2	-5.2	-6.3
0.5	-2.4	-4.7	-5.4	-6.6	-7.8

4.5 Conclusions

The transition from fossil fuel based energy consumption towards more sustainable energy solutions is a complex societal process. Making investment decisions in such a dynamic, complex environment with different sources of risk is challenging. It is widely acknowledged that such multi-stage capital investment projects can best be evaluated using a compound option model, where every investment phase creates an option for investment in the next phase. The value of the early phases derives not so much from their expected cash flows as from the follow-up opportunities they may create.

In this chapter, I start with an N-fold compound option model that incorporates market and technical uncertainty. However, the introduction of new energy technologies such as hydrogen needs government support. Political support increases the expected future return from the project and will accelerate the adoption of hydrogen-fuelled vehicles and the construction of the required infrastructure. Yet, public policy support is not a given, especially since the long horizon of such project usually extends beyond periodic elections and across different ruling political parties or coalitions. Consequently, policy uncertainty is a fact of life. It includes lack of clear policy goals, lack of long-term commitment to policy goals, and lack of clear procedures and regulations, as well as changes in these factors.

Therefore, I focus on the role of policy uncertainty as a separate and important source of risk, parallel to market and technical uncertainty, and apply it to the case of the rollout of a new hydrogen infrastructure in the transport system. I model policy uncertainty as a Poisson jump process and investigate its importance in project valuation through varying two key parameters: the frequency and the expected size of the jumps. Note that the jumps reflect policy changes.

Overall, I find that a project that would be feasible when only market and technical risk are considered can become infeasible when policy uncertainty is incorporated. This is not the case when policy uncertainty is symmetric. If policy shocks with a positive and negative impact on the project value are equally likely, the upward potential of future positive policy shocks outweighs the value reduction from negative shocks. In that case, the project actually becomes more attractive. However, if negative shocks are dominant in size or frequency, policy uncertainty may prevent otherwise attractive and desirable investments. Obviously, for investors it is important to correctly assess the characteristics of policy uncertainty. Policy makers need to be especially aware that uncertainty with respect to negative policy shocks can be an important impediment to large investments in risky new technologies and infrastructure projects. To encourage such investments, it appears important to formulate clear policy goals and instruments as well as to design a clear regulatory and institutional framework. Moreover, a credible commitment to keep policies in place over a long period is crucial, too. In such a setting, where policy uncertainty is reduced to very low levels, market and technical uncertainties will be main drivers of investment decisions.

Chapter 5
Hydrogen-Fuel Infrastructure Investment with Endogenous Demand: A Real Options Approach[26]

5.1 Introduction

Real option modelling has become an increasingly popular approach for the valuation of large infrastructure projects as well as the valuation of innovative projects in technology-intensive industries in recent decades. Examples that apply real option valuation to natural resources and energy problems include Santos et al. (2014), Sarkar (2009), and Pless et al. (2016). Zhou et al. (2010) and Eckhause and Herold (2014) used real option methods to determine optimal funding and optimal subsidies in the field of sustainable energy.

The real option approach is preferable to net present value computations because it takes into account the value of waiting and operational flexibility: even with a negative NPV now, the project still may be profitable at a later point in time. Put differently, NPV may tend to undervalue a project. To operationalize the real option approach – or the NPV method for that matter – assumptions have to be made about the future demand for the new product or technology and the speed at which adoption will take place. In many applications, future demands are modelled exogenously and independently from the availability of the necessary infrastructure; see for instance Engelen et al. (2016) for the case of hydrogen investment.

In reality, the assumption of exogeneity of future demand may be unwarranted in some cases, especially when a costly infrastructure is required to successfully introduce a new technology. In such case, the speed and degree of adoption of the new technology may well depend on the availability of the infrastructure.[27] If so, an investment problem with chicken-egg characteristics may emerge: without sufficient infrastructure, consumers will not adopt the new technology, but without (likely) adoption, investors will not build the infrastructure. Put differently, supply and demand are interdependent. Obviously, appropriate modelling of the investment decision problem then needs to take this interdependency into account.

In this chapter, I aim to contribute to the literature by explicitly incorporating the impact that realized

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[26] This chapter has been published as a TKI discussion paper: https://www.uu.nl/en/file/55371/download?token=MJ-M6HPZ.

[27] Reid et al. (2016) recently argued that lack of re-charging infrastructure is one of the major hurdles facing the adoption of plug-in electric vehicles.

investment in new infrastructure has on adoption speed in a real options framework, and by analysing the consequences of this dependence for optimal investment. This way, I jointly model the interdependency of demand and supply. To model the adoption process, I use a Generalized Bass Model – GB model – (see Bass, Jain, and Krishnan, 1994), which is frequently used in business and marketing studies for the analysis of new products and technologies.

Subsequently, I illustrate the relevance of combining the GB model with the real options approach by applying it to the hydrogen case. It is generally acknowledged that the introduction of hydrogen-fuelled cars would imply an expensive and time-consuming transition process involving a high degree of uncertainty, for instance with respect to technology, changes in government support and regulation, and future demand (Zhao and Melaina, 2006). Corresponding to the concept behind the GB model, I focus in particular on demand uncertainty and its dependence on the available supply of infrastructure. During the transition period, there is a significant challenge in matching the scale and timing of the fuelling infrastructure investment with the actual hydrogen demand. Entry commitments involve sacrificing flexibility and increasing exposure to the uncertainties of new markets.

Theoretically, from the infrastructure provider's cost perspective it is important that there are just enough stations to ensure satisfactory utilization of each station and keep the cost as low as possible. An underutilized station drives up costs significantly. From a revenue perspective, the infrastructure investor aims at realizing a high adoption speed. For potential adopters, it is equally important that the number of refuelling stations is more than sufficient. That is, consumers will perceive adequate refuelling availability over a sufficiently large refuelling coverage area as an important factor in their decision whether to switch to hydrogen cars.[28] This implies a choice between having higher fixed costs initially by building more stations at faster speed in combination with higher potential revenues due to higher and faster adoption on the one hand, and investing at a slower speed with lower costs but also slower expected growth of revenues on the other. Deciding on a fast build-up of infrastructure will raise initial losses. Of course, it would be possible to pass through these costs into the price of hydrogen fuel, but that would make adoption less attractive in turn.

In particular, in our application I make the diffusion process – which models future demand – a function of the number of available refuelling stations. Estimating this GB model for the hydrogen case directly is infeasible due to the lack of realized data. Instead, I do a scenario analysis where I combine six different investment strategies with four different parameterizations of the GB model. The variation in

[28] In addition to infrastructure investors and consumers, car producers are the third party that has to optimize an investment decision. For simplicity, I do not take this into account in the analysis.

parameterization captures different degrees of demand sensitivity to existing infrastructure. The exploratory research will shed light on the way the optimal investment path depends on the sensitivity of demand to available infrastructure and the consequent process of market penetration, and provide direction for investors, policymakers and decision-makers.

The chapter is structured in the following way. The next section introduces the concept of innovation diffusion and concisely reviews the literature on modelling diffusion processes. In section 3, I briefly summarize the setup of the hydrogen investment case for the Netherlands. I develop the specific GB model, which allows us to incorporate the sensitivity of demand to existing infrastructure in the optimal investment decision. Section 4 contains a scenario analysis based on the GB model to investigate the way the feasibility of investment depends on the sensitivity of demand on existing infrastructure. Section 5 concludes.

5.2 Innovation diffusion and market adoption

In this section, I introduce the concept of innovation diffusion and market adoption. In section 2.1, I first provide a broad graphical introduction using a stylized and simple diffusion process as presented by Rogers (1983), and discuss some of the complicating factors. In section 2.2, I briefly review the different strands in the literature with respect to the modelling of diffusion processes where I distinguish between the "aggregate" approach and the "individual choice" approach. Section 2.3 elaborates on the modelling strategies in the literature using the aggregate approach, as it fits the framework of our setup best.

For expositional reasons, the description and presentation of the diffusion process is kept simple and suggests innovation and adoption proceed at a predictable and linear pace. In reality, innovation processes can be highly non-linear and can be characterized by feedback loops and interactions between different phases. In this article I abstract from such complexities.

5.2.1 A stylized diffusion process

The origin of new technologies usually lies in principles and concepts found by doing fundamental research. The adoption process typically begins by entering tiny niche markets. After that, the new technologies are validated in the demonstration phase: some of the technological uncertainties are resolved and much attention goes to integrating the technology in existing systems (e.g. integrating fuel cells in cars) and to reducing the complexity of the technology. When demonstrations are successful, the scale of demonstration projects may gradually increase. With the scale of projects, the financial risks also increase, especially because the future prospects of the technology may still be unclear. After the pre-commercialization phase, a technology moves into its early market phase. It starts to be of commercial interest for a specialized set of users, willing to take on a novel beneficial technology at slightly higher costs. The technology's market share may still increase and eventually the technology may become one of the incumbents, coexisting with, or even pushing out older technologies.

Figure 5-1: Cumulative adoption path

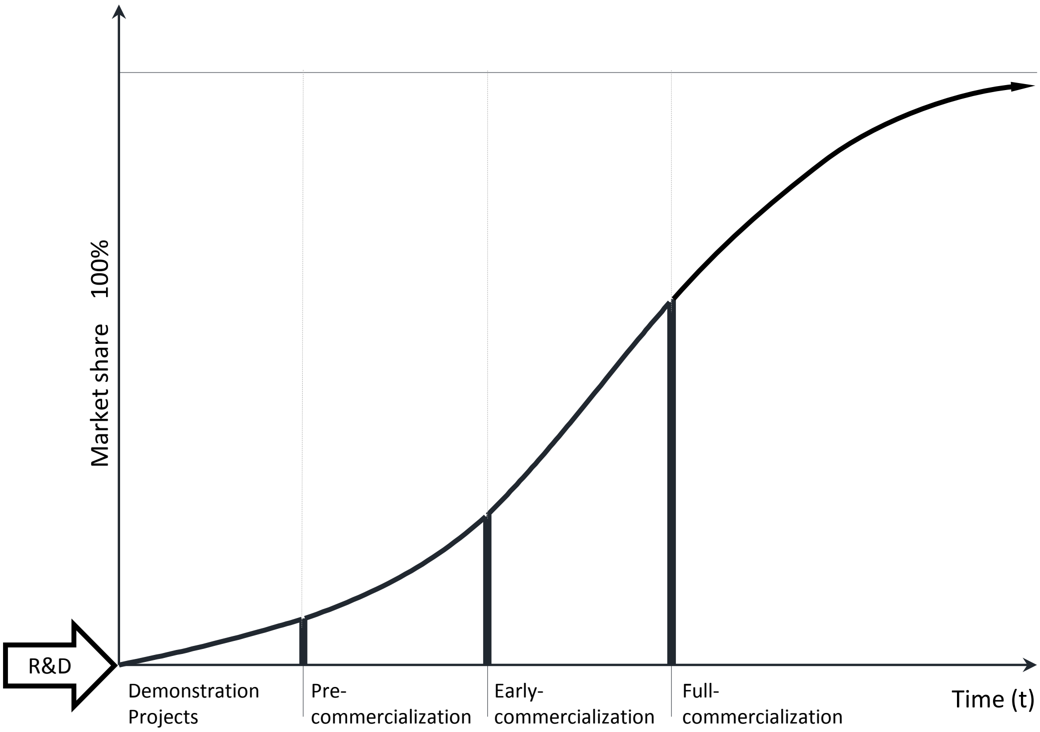
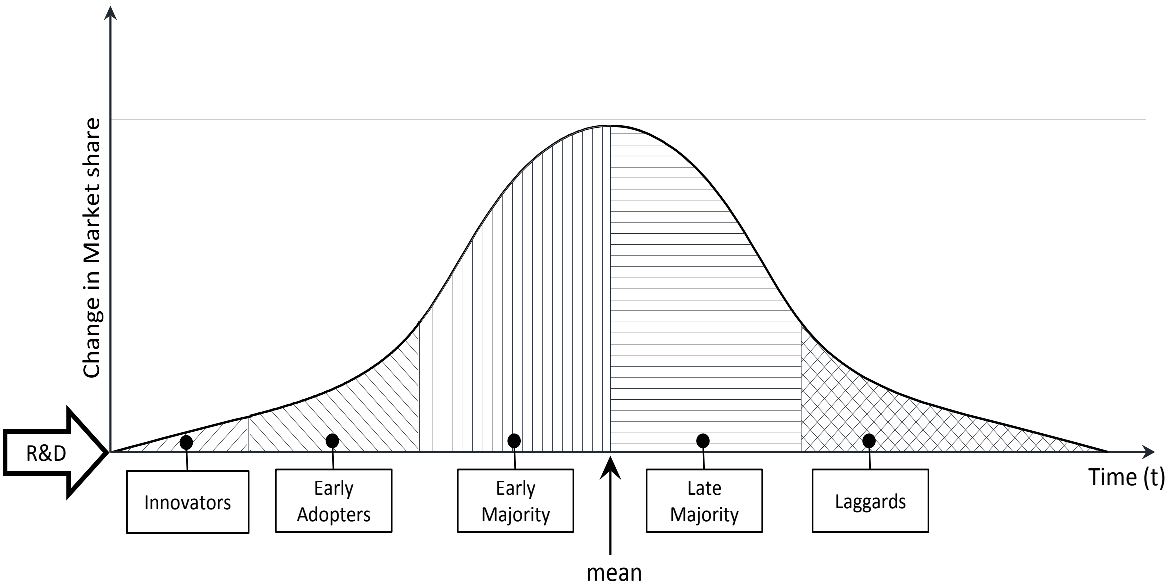


Figure 5-1 is adapted from Rogers (1983). The S-shaped curve plots the market share of an innovative technology against time or the amount of invested capital: slow initial improvement, then accelerated improvement, then diminishing improvement. These stages can be linked to the concepts of pre-commercialization, early commercialization and full commercialization indicated by the bold vertical bars. The S-curve can be used to gain insight into the relative payoffs of investment in competing technologies, as well as in providing some insight into when and why some technologies overtake others in the race for dominance.

Figure 5-2: Characterization of adopter groups



While the S-shaped curve shows cumulative adoption as a percentage of market potential, the bell-shaped curve in Figure 5-2 is a stylized way to reflect the adoption over specific periods. Rogers (1983) used a similar figure to classify adopters of an innovation according to the timing of their adoption, under the assumption that the new technology eventually captures a 100% of the market. He defines the adopter categories on the basis of the normal distribution with the mean equal to the mean time to adoption t_{mean}. The innovators (2.5%) are the ones that adopt earlier than the mean time minus two times the standard deviation σ, the early adopters (13.5%) start using the new technology between $t_{mean} - 2\sigma$ and $t_{mean} - \sigma$, the early majority (34%) adopts between $t_{mean} - \sigma$ and t_{mean}, the late majority (34%) between t_{mean} and $t_{mean} + \sigma$, and the laggards (16%) finally adopt after $t_{mean} + \sigma$.[29]

Overall, diffusion paths can and will be much more complex than the stylized curve in Figure 5-1 and Figure 5-2. Mahajan et al. (1990) criticized Rogers for the too rigid assumptions in his approach. They convincingly argued that in many cases the adoption process does not follow a normal distribution. In addition, there is no a priori reason why the percentages of different type of adopters – innovators, early adopters etc. – would be the same for all new products and technologies. Therefore, they pleaded for the use of more general and flexible diffusion models to analyse adoption. Note that estimating potential market size in advance presents another complication in distinguishing different adoption groups.

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[29] With respect to the adoption of innovative (smart) energy systems to promote sustainable energy use, Noppers et al. (2016) showed that symbolic attributes – the degree to which innovations say something about the adopting person – provide a powerful explanation of the distinction between adopters and non-adopters.

Many technologies actually do follow the S-shaped pattern as depicted in Figure 5-1, but the exact shape of the S-curve (and possible asymmetries) differs among technologies. Unexpected changes in market demand, policy and regulation, component technologies, or complementary technologies can shorten or extend the lifecycle. Moreover, investors can actively influence the shape of the S-curve through the nature of their development; see for example Golder and Tellis (1997).

5.2.2 Modelling diffusion processes

Since the late 1960s, a large literature has emerged on modelling diffusion paths for new products and technologies; see Mahajan et al. (1990) and Peres et al. (2010) for detailed overviews. Generally speaking, there are two broad approaches to model diffusion paths for new products and technologies. First, there is the "aggregate approach" to modelling diffusion. It implicitly assumes that the social system is homogeneous and adoption of a new product or technology is dominantly driven by consumer interaction, that is, by "word-of-mouth". The seminal model in this line of research was introduced by Bass (1969) and has been modified and augmented in many ways since. In this model, the focus is on the total number of new adopters in a given period where all individual non-adopters at the time have an identical probability to adopt. The advantage of the approach is that it allows parsimonious modelling on a macro-level, requiring little data. The disadvantage is that it does not shed light on the underlying trade-off an individual makes when deciding to adopt or not, and ignores the possible influence of individual factors in this decision.

Second, a more recent line of research recognizes the potential role of consumer heterogeneity and gives it a central role in the diffusion process. In this research individual agents optimize some utility or benefit function, conditional on a number of individual constraints and preferences, on product and technology characteristics, and possibly subject to uncertainty as well. Obviously, the probability to adopt then will differ across agents. Apart from allowing for adoption heterogeneity, the approach also has the advantage of allowing for interdependencies between agents through network effects, and of allowing the analysis of spatial diffusion. However, the approach faces substantial challenges, too. The utility function and decision rule need to be chosen, and an aggregation procedure has to be constructed to translate the myriad of individual decisions into a macro framework. Often this approach combines elements like multi-agent (Schwoon, 2006), complex system (Struben and Sterman, 2007) and game theory (Smit, 2003). Köhler et al. (2009) and Huétink et al. (2010) used agent-based modelling techniques as a framework for assessing possible pathways of the transition to a sustainable mobility society. Meyer and Winebrake (2009) used system dynamics modelling to analyse the complementary vehicle-infrastructure relationships exhibited in a hydrogen transportation system.

5.2.3 *Aggregate diffusion models*

Aggregate diffusion models are used extensively in marketing, business studies, and policy research to provide forecasts of adoption (demand) for new (durable) consumer products as well as new technologies.[30] The models focus on the macro population level and are based on the overall statistical behaviour of potential adopters. I start our discussion with the Bass model (Bass, 1969), which – together with its broad offspring – is the most widely accepted, used and cited model in the field (Mahajan et al., 1990). In the Bass model, the expected adoption of the new technology can be presented using a simple differential equation. For the moment, I use continuous time notation:

$$\frac{dK}{dt} = p[\bar{K} - K_t] + \frac{q}{\bar{K}} K_t[\bar{K} - K_t] = \left[p + \frac{q}{\bar{K}} K_t\right][\bar{K} - K_t]. \qquad [5\text{-}1]$$

In Equation [5-1], K_t refers to the number of adopters at time t, and $\bar{K}$ equals the ceiling or potential amount of adopters for the given technology. The equation states that in a short period, a constant fraction p of the non-adopters is expected to start using the technology. In addition, new adoption depends on the amount of agents that already have adopted the new technology, governed by the expression $qK_t/\bar{K}$. This latter term captures the impact of the consumer interaction, or the network effect. Alternatively, the Bass model can be written as

$$y_t = \frac{dY}{dt} = [p + qY_t][1 - Y_t], \qquad [5\text{-}2]$$

where $Y_t = K_t/\bar{K}$. While Equation [5-1] was expressed in absolute number of adopters, it should be noted that Equation [5-2] is expressed in adoption percentage. Y_t is the – expected –cumulative percentage of adopters at time t, which will approach one as time evolves. The time derivative of Y_t, expressed as y_t, is the probability density function representing the instantaneous likelihood of purchase at time t. It is only based on the two diffusion parameters p and q, and on $(1 - Y_t)$, the percentage of non-adopters at time t. In the literature, p is typically referred to as the "coefficient of innovation" or the "external influence". It gives the proportion of the current non-adopters that will switch to the new technology per unit of time, independent of the current adoption success. In the standard Bass model, p is assumed to be constant. The parameter q is generally referred to as the "coefficient of imitation" or the "internal influence" and is assumed constant as well. It captures the

[30] A recent application in the energy field is Shin et al. (2016), who used a diffusion model to forecast demand for carbon capture and storage (CCS) technology.

communication or network effect in the adoption process. It can be easily shown that both Equation [5-1] and Equation [5-2] have a closed-form solution.

Using the elegant and successful Bass model as a starting point, the literature shows an impressive proliferation of extensions and refinements. I refer to Easingwood, Mahajan and Muller (1983) for an overview of early day diffusion model characteristics. On the one hand, a number of approaches simplify the Bass model by assuming the coefficient of innovation p to equal zero; see for instance Fisher and Pry (1971). On the other hand, the literature criticizes the Bass model for being too restrictive in its assumptions. Easingwood et al. (1983) pointed out that the Bass model is quite rigid in i) assuming the parameter q to be constant regardless of the degree of penetration arrived at already, ii) confining the inflection point of the S-curve – that is, the point at which the rate of adoption is highest – to be below but close to 50%, and iii) assuming a perfectly symmetric diffusion pattern before and after the inflection point. In their view, this puts severe limits on the applicability of the Bass model. As an alternative, Easingwood et al. (1983) proposed a logistic diffusion model – labelled a non-uniform influence (NUI) model – which leads to Equation [5-3]:

$$y_t = \frac{dY}{dt} = \left[p + qY_t^{\delta}\right][1 - Y_t]. \qquad \textit{[5-3]}$$

When δ equals one, the model converges towards the Bass model. However, for δ not equal to one, different diffusion paths arise with a time-varying coefficient of innovation, and faster or slower adoption depends on the value of δ and asymmetric effects. If $0 < \delta < 1$, it causes an acceleration of influence leading to an earlier and higher peak. If $\delta > 1$, it causes delay in influence leading to a lower and later peak. In empirical applications both examples of high and low δ values are found. In Easingwood et al. (1981), this logistic model is used in restricted form with $p = 0$ to allow for a convenient closed-form solution.

Another line of criticism focuses on the lack of attention in the basic Bass model for underlying economic drivers of the adoption process. The Bass model imposes a semi-automatic process where only the previously achieved degree of adoption can influence the probability of new adopters. However, from an economic perspective, one would expect marketing effort and price to be important determinants of the speed at which agents are willing to adopt a new product or technology. Moreover, the same factors could also have an impact on the market potential. In terms of the Bass model, p, q and $\overline{K}$ all could be functions of such drivers. Examples of models that endogenize market potential $\overline{K}$ are Kalish (1985) and Kamakura and Balasubramanian (1987). Horsky and Simon (1983) are a good example of modelling the probability of adoption as a function of marketing effort. Bass et al. (1994) provided an extended overview of diffusion models that include price and/or advertising as economic fundamentals.

In an attempt to integrate the above criticism into the standard Bass framework, Bass et al. (1994) proposed the GB model. It is a generalization of the basic Bass model, which allows the inclusion of decision variables (such as price and advertising) but maintains the basic shape of the diffusion curve. The GB model has the following form:

$$y_t = \frac{dY}{dt} = [p + qY_t][1 - Y_t]x_t, \tag{5-4}$$

where x_t may be a function of decision variables such as marketing effort and price. Note that Equation [5-4] can be easily rewritten as follows:

$$y_t = \frac{dY}{dt} = [px_t + qx_tY_t][1 - Y_t] = [p^*(x_t) + q^*(x_t)Y_t][1 - Y_t]. \tag{5-5}$$

Equation [5-5] again looks like the basic Bass model with parameters p^* and q^*, which are functions of x_t. The main difference is that these two parameters now are time-dependent functions of potentially one or more economic drivers. Compared to other models that directly model the impact of economic decision variables on the adoption rate, Bass et al. (1994) imposed the extra restriction that p^* and q^* have exactly identical time-dynamics, given by x_t. Theoretically, there appears to be no clear reason why one would assume the rate of innovation (p^*) and the rate of imitation (q^*) to respond similarly to changes in price or advertisement.

Bass et al. (1994) operationalized x_t as follows:

$$x_t = 1 + \beta_1 P'_t + \beta_2 A'_t, \tag{5-6}$$

where P is price and A is marketing effort (spending). Then, P'_t is the rate of price change and A'_t the rate of change in advertising spending at time t. The GBM model has the appealing property that both price and advertising can be incorporated in the diffusion process, while still allowing the model to reduce to the basic model in case the rate of change of P'_t and A'_t are approximately constant. Actually, Bass et al. (1994) claimed the basic Bass model works so well in many applications because the price and advertisement development is rather smooth allowing parameters p and q to capture the effect of economic drivers on the rate of adoption.

Obviously, the GBM model has general potential and can be applied to a wide range of innovations. In this chapter, I provide an illustration by applying it to the case of the introduction of infrastructure for hydrogen cars in the Netherlands. Using a simulation analysis, I focus on the consequences of incorporating the interdependence between the development and rollout of a hydrogen infrastructure and the adoption of hydrogen cars by consumers for the investment decision in infrastructure.

5.3 An application to the case of hydrogen infrastructure in the Netherlands

In this section, I first introduce the setup of the hydrogen infrastructure project in the Netherlands; see also Engelen et al. (2016). Subsequently, I develop and discuss the adaptation of the GBM model to this particular case. In particular, how I model the sensitivity of hydrogen cars to an available hydrogen infrastructure is shown.

5.3.1 Description of the hydrogen infrastructure project

The setup of the hydrogen infrastructure project is loosely based on the EU HyWays (2008) project. It lays out a phased roadmap for hydrogen stations in 10 European countries, viz. Finland, France, Germany, Greece, Italy, the Netherlands, Norway, Poland, Spain, and the United Kingdom (HyWays, 2008). This hydrogen energy roadmap distinguishes the following four settings with respect to policy support and technical learning: ‘baseline’, ‘modest policy support and modest learning’, ‘high policy support and high learning’, and ‘very high policy support and high learning’. Here, I take the ‘modest policy support and modest learning’ setting as our starting point.

The roadmap also assumes a number of stages. Phase I (2010-2015) is a small-scale experimental (pre-commercial) phase that brings up to 10,000 hydrogen vehicles to European roads. Phase II (2015-2020) is the early commercial phase. The roadmap assumes that in the early commercial phase, three to six early user centres will be developed in each country. For the Netherlands, these are the regions around Amsterdam, Rotterdam and Nijmegen (see Engelen et al., 2016 for an application on a regional scale). The ambition is to link these national centres through so-called hydrogen corridors. Subsequently, national-wide networks will be rolled out. With respect to the number of required stations, the HyWays roadmap assumes that in the early commercial phase about 400 stations will be necessary in the early user centres plus another 500 to facilitate the hydrogen corridors. In the full commercialization stage III, an increase to 4 million between 2020 and 2025 and to 16 million hydrogen cars after 2025 is estimated. In the final stage after 2025, 13,000 to 20,000 stations ultimately will be needed to serve ten million hydrogen vehicles.[31]

All of the above numbers are for the total of 10 participating countries, so I need to scale those numbers to obtain estimates for the Dutch market. When measured in terms of the number of users, the Netherlands account for 3.34% of the total target population in the EU, while measured in kilometres of roads they account for 3.95% of the EU total (Stiller et al., 2008). Taking 4% as the approximate proportion of the Netherlands within the HyWays project, this would correspond to 400 hydrogen cars by 2015, 20,000 cars by 2020 and a further growth to 640,000 after 2025. With respect to the number of stations, the HyWays setup implies that about 30 stations would be built by 2015 and 800 by the end of phase III. At the end, there would be 800 stations in the Netherlands serving about 640,000 cars.[32]

The timing of achieving those target numbers is dependent on the specific setting underlying the scenario. In our analysis, I take a 34-year horizon. In our analysis, I choose the pre-commercial phase I to run from 2010 until 2014. It is comprised of technology refinement and market preparation. The early commercialization phase II is from 2015 until 2024 and the full commercialization phase III from 2025 until 2044. In the real option analysis, I use a proxy for the cash flows after 2044. Subsequently, I design six different strategies with respect to the timing of investment in infrastructure, leading to different speeds of construction for the refuelling stations. In all scenarios, the final number of 800 stations is reached in 2044. Furthermore, I assume demand (adoption) to be governed by a Bass model. In the basic Bass model where the number of available stations rises linearly from zero to 800 in 34 years, the number of users in the Netherlands is estimated to be about 15,000 in 2014 and to slightly increase above 200,000 by 2024 to approach 640,000 in 2044.

For some intuition behind these different phases, consider the following. Generally, the introduction of an innovative technology leads to early adoption by enthusiasts. In this case, the pre-commercialization phase would be attained when enough hydrogen stations are in place to satisfy the refuelling needs of many early adopters. These consumers will be somewhat more willing to be inconvenienced by driving out of their way to refuel with hydrogen. Early-commercialization phase is attained when enough hydrogen stations are in place to satisfy a larger portion of the general population. High volume sales to the general public take place in the final full-commercialization phase. Since many consumers want to

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[31] The roadmap also assumes the size of the stations to increase over time, from single dispenser stations in the early phases to large multiple dispenser stations later on. In our analysis, I abstract from this complication.

[32] In reality, the objectives of the HyWays scenario have not been realized so far and the project considerably lags behind the 2008 expectations. I nevertheless use its assumptions and original time path for the setup and simulations in this paper.

be able to drive long distances and do not want to be confined to a specific area, a local infrastructure probably will not suffice in this stage anymore. To overcome range anxiety, at least a coarse national network would have to be in place.[33]

The advantage of a multi-phased process is that it allows staged investments and investment decisions. Moreover, it makes a real option analysis an attractive and appropriate approach to assess the attractiveness of the investment. Each stage can be viewed as an option on the value of subsequent stages and valued as a compound option (Cassimon et al., 2004). It is important to note that phase III (full-commercialization) cannot proceed without the execution and successful completion of phase II, which itself will only take place upon the successful transition from phase I. The end points of phases I and II thus represent decision times, in addition to the starting decision at the beginning of stage I for the investor in hydrogen infrastructure. A positive continuation decision at that time requires the option value of the future project to exceed the extra investment required to enter the next phase. If not, the project will be terminated.

To calculate the expected operating cash flows for each project phase, I need to estimate the present value of the expected operating revenues R_t less operating expenses C_t, which requires a number of assumptions with respect to the input values of all parameters of the cash flow model. To calculate hydrogen demand for fuel cell passenger vehicles, I assume that each vehicle will use approximately 0,7 kg of hydrogen each day, amounting to 255,5 kg per year. For an average fuel cell vehicle with a fuel economy of 80 to 96 kilometres per kg, this would accommodate about 56 to 64 kilometres of driving on an average day (Ogden, 1999; CaFCP, 2008). For hydrogen fuel to be competitive with fossil fuels, the literature generally assumes a retail price of €10/kg (Benthem et al., 2006).[34] Although hydrogen is much cheaper produced from natural gas, the production process is always associated with the emission of greenhouse gases and local pollutants (Haryanto et al., 2005). Sustainable hydrogen cost is initially about €5/kg (phase I), but due to technical learning, I assume it will gradually decrease to €4/kg in phase II and a long-term production cost of €3,4/kg in phase III (adapted from Lebutsch and Ieda, 2011 and Benthem et al., 2006). This includes all the relevant expenses, for instance, transportation to the refilling station and carbon capture and storage (CCS) costs if necessary. After 2044, annual operational cash flows are assumed to remain constant forever. Their present value in 2044 is used in the computations as the residual value of the investment.

[33] Similar developments are seen in the electrical vehicles market.

[34] I take into account the regular fuel taxes in the Netherlands such as excise duty and VAT, which lowers the net retail price to €4/kg.

For the computations, I furthermore use a 25,5 percent marginal tax rate (KPMG, 2011), an average Eurozone inflation rate of 2,24% (ECB, 2011), a 1,13% real interest rate, a 21,21% net working capital requirement in a given year (as percentage of the sales) (Damodaran, 2011), and a straight-line depreciation over the 20 year economic life of each station. I use a risk-adjusted discount rate of 8% for calculating the NPV of the project cash flows.[35]

Each stage also requires investments in the necessary amount of hydrogen fuel stations in order to operate the fuel network. The cost of a hydrogen fuel station depends upon many factors, including the type of station, location, equipment manufacturing volume and continuing technology advancements. Here, I base our assumptions on Lebutsch and Ieda (2011). I assume a standard hydrogen station initially costs €0,95 million. Unit investment costs will decrease over time as a result of economies of scale and learning. To reflect this, I specify the cost function as $\varpi(N) = \alpha \cdot N^{-b}$, where $\varpi(N)$ is the investment cost of the Nth unit, b is a learning parameter and α the investment cost of the first unit (€0,95 million). I choose b to be equal to 0,0465, so that the unit costs decrease to €0,70 million by 2044. The average investment cost to build N fuel stations will therefore be equal to $I = \alpha \cdot \int_1^N N^{-b} dN$. Fixed one-time installation costs amount to 30 percent of the unit costs, and annual maintenance costs are 3,5%. Additional labour costs are €0,5mln per year.

5.3.2 The Model

In our application, I will start from the GBM model in Equation [5-4]. However, rather than assuming that x_t is a function of price and marketing effort, I assume x_t is a function of availability of refuelling stations. Put differently, I hypothesize that potential buyers of a hydrogen car – adopters of the new hydrogen technology – will be more inclined to actually buy the car when they know there will be sufficient refuelling stations in the region they intend to drive the car. Specifically, I propose

$$x_t = 1 + \beta \frac{N_t - \bar{N}_t}{\bar{N}_t}, \qquad [5\text{-}7]$$

where N_t equals the cumulative number of refuelling stations that have been built up to year t, and $\bar{N}_t$ equals the cumulative number of refuelling stations that would have been built up to year t when the same amount of stations would be built every year over the complete 34 year planning horizon. The gap in Equation [5-7] then indicates how far the actual building – investment – strategy deviates from the

[35] This cost of capital corresponds to the 2010 sector averages of oil and gas distribution (7,19%), environmental (7,62%), natural gas (8,07%), power (8,23%), automotive (8,58%) and chemical (8,88%). Numbers are taken from Damodaran (2011).

constant investment path. Note that when actual investment exactly follows the linear trend, the gap will be zero and x_t will equal one for the whole period. In this "neutral" scenario, the model reduces to the basic Bass model, consistent with the argument of Bass et al. (1994).

Further, I define β as the diffusion coefficient that controls the effect of available stations in accelerating and decelerating the diffusion process. The motivation behind this setting is to reflect the importance of refuelling infrastructure investments on the market penetration of hydrogen cars. When β equals zero, the sensitivity of adoption to realized stations is zero and the model reduces to the standard Bass model. The higher β is, the stronger the effect of early investment on adoption. I will use the combination of Equations [5-1], [5-4] and [5-7] in our scenario analysis, using different paths for N_t and different parameter values for β. The overall equation then is

$$\frac{dK}{dt} = \left[p + \frac{q}{\bar{K}} K_t\right] [\bar{K} - K_t] \cdot [1 + \beta \frac{N_t - \bar{N}_t}{\bar{N}_t}]. \qquad [5\text{-}8]$$

5.4 A Scenario Analysis

Direct estimation of a simple Bass model or an extended GB model for the hydrogen case is infeasible due to the lack of actual data on infrastructure investment and consumer adoption. This is similar to many previous disruptive technologies prior to market entry (Hardman, Steinberger-Wilckens and van der Horst, 2013). For that reason, I focus on a scenario analysis.

As discussed previously, I assume that the rollout of an infrastructure for hydrogen fuel cell vehicles will cover the period 2010-2044. In these 34 years, I assume 800 fuelling stations will be built to service a maximum capacity of 640,000 vehicles $\bar{K}$. However, the timing of the building process is taken as a free parameter here. The purpose of the scenario exercise is to investigate the impact of different speeds at which the stations are built on the potential profitability of the overall project, taking into account the impact of the building strategy on the adoption speed of hydrogen cars in the market.

I do this by embedding the GBM model of Equation [5-8] into the real option framework. In the following section, I define six plausible investment scenarios, distinguished by the speed at which refuelling stations are built. The GBM model pins down the diffusion process of adoption through three parameters p, q and β. For p and q I use constant values across all scenarios, calibrated on the HyWays (2008) characteristics. For β I use four different parameter values, reflecting different demand sensitivities with respect to the availability of infrastructure. The higher β is, the more weight potential users attach to having easy access the refuelling infrastructure in their adoption decision. The results will shed light on the way the optimal investment (building) strategy depends on the sensitivity of adoption to available infrastructure.

5.4.1 Scenario assumptions

I take a two-step approach. First, I outline the six different scenarios, and subsequently elaborate on the choice of p, q and β.

I start from the so-called 'neutral' scenario – henceforth labelled Neutral. This is the base scenario in which the stations are built at constant speed over the whole 34-year period. It is constructed as a neutral, steady increase scenario. That is, every year about 24 stations (=800/34) are added to the existing stock of stations. It follows from Equation [5-8] that in the 'neutral' scenario the diffusion process will take the typical S-shaped Bass distribution. In this case the gap variable in x_t is zero throughout the whole period regardless of the value of β because the investment gap $\frac{N_t - \bar{N}_t}{\bar{N}_t}$ is zero.

Subsequently, I design a number of other scenarios in which the building speed differs from Neutral[36] Four scenarios follow a similar pattern, with a linear (constant speed) build-up until 2024 and a second linear path between 2024 and 2044. Cautious has a very slow start with only 50 stations built in the first fourteen years. As a result, building speed has to pick up substantially to build the remaining 750 stations between 2025 and 2044. In Conservative, the number of stations built in the first fourteen years doubles to 100 (compared to Cautious). In Confident, again a doubling takes place, to 200 in the first fourteen years. Note that all of these scenarios still build at a lower speed initially than Neutral. In Neutral, 329 stations are built between 2010 and 2024. Aggressive is the mirror image of Confident relative to Neutral. In Aggressive, 460 stations are built in the first fourteen years, which is as much more relative to Neutral as Confident is less. Finally, Catch-up starts with the same speed as Confident, but accelerates after ten years (in 2020) until it reaches the level of Aggressive in 2034 where it slows down again to follow the latter path.[37] Table 5-1 provides an overview of the build-up per scenario.

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[36] Obviously, an infinite number of scenarios are possible. I have chosen a grid that allows me to bring out the most important conclusions.

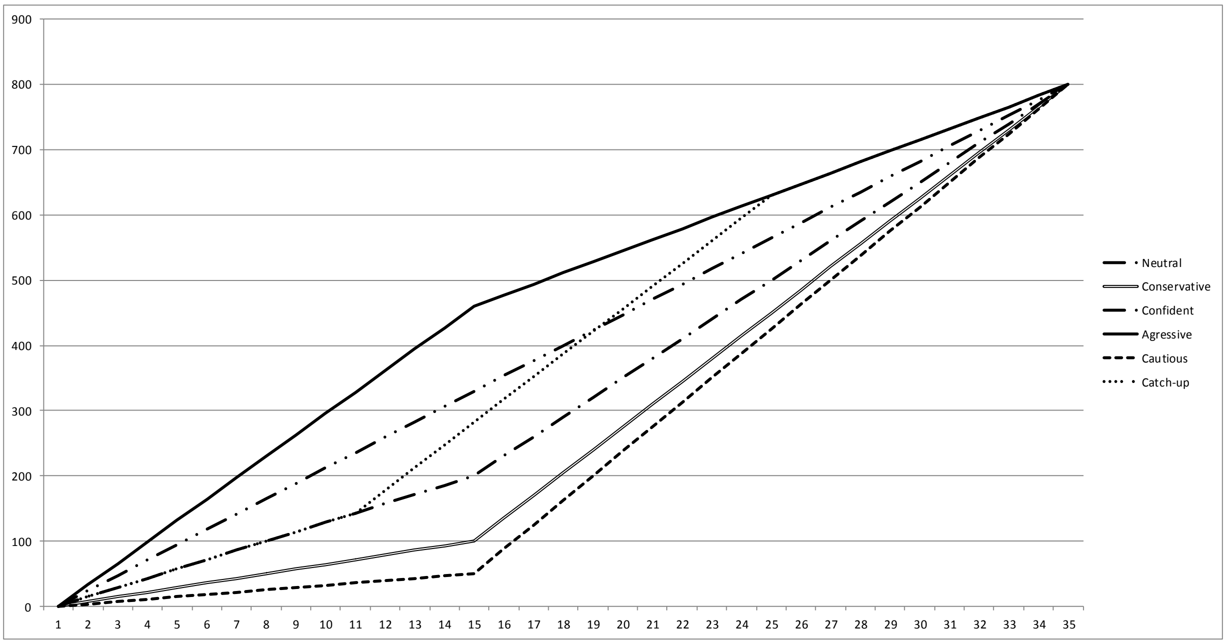
[37] The building strategy in the *Conservative* scenario roughly equals that of HyWays (2008).

__Table 5-1: Building speed per scenario and regime (new stations per year)__

Scenario	Timing of the build-up (in new stations per period; in each period, the build-up is linear)					
	Period 1-34	**Period 1-14**	**Period 14-34**	**Period 1-10**	**Period 10-24**	**Period 24-34**
Neutral	800	(329)	(471)	(235)	(330)	(235)
Cautious		50	750			
Conservative		100	700			
Confident		200	600			
Aggressive		460	340			
Catch-up				143	487	170

Note that the regime changes in the different scenarios do not necessarily coincide with the decision years 2014 and 2024 in the real option analysis. However, I will evaluate all scenarios on the basis of these decision points for the infrastructure developer. Figure 5-3 provides a graphical illustration of the different investment strategies and corresponding growth of the number of refuelling stations in the different scenarios.

__Figure 5-3: Number of Stations in Each Scenario__



I now turn to the parameterization of the model. Obviously Bass type models have been used extensively in the literature to model the diffusion of new products and technologies. Many empirical applications are available especially for consumer durables; see for example Bass et al. (1994), Easingwood et al. (1983) and Srinivasan and Mason (1986). Estimates for p typically are in a range from 0 to 0.04, while estimates for q range from around 0.20 to about 0.70. In some applications the ceiling $\bar{K}$ is pre-specified, in others it is estimated as an extra parameter. Estimation methods include simple OLS, Maximum Likelihood Estimation (MLE) and non-linear least squares (NLS). I refer to Srinivasan and Mason (1986) for a comparison and discussion. Additionally, estimation typically requires reformulating Equation [5-1] or [5-8] in discrete time. The discrete version of Equation [5-8] looks as follows:

$$dK_t = K_t - K_{t-1} = \left[p + \frac{q}{\bar{K}} K_{t-1}\right] [\bar{K} - K_{t-1}] \cdot [1 + \beta \frac{N_{t-1} - \bar{N}_{t-1}}{\bar{N}_{t-1}}]. \quad \textit{[5-9]}$$

It allows for the estimation of 4 parameters, p, q, β and $\bar{K}$. When β is set to zero, the model reduces to the standard Bass model with three parameters to be estimated.

I calibrate the parameters p and q in Equation [5-9] at 0.025 and 0.275 to allow the diffusion process to converge gradually towards the potential adoption level $\overline{K}$ (640,000) by the year 2044. These values fall into the range usually found when estimating the Bass model. For β, I choose four different values reflecting differences in the sensitivity of demand to the availability of refuelling stations using the GB model. In particular, I consecutively set the value of β equal to 0, 0.25, 0.50 and 0.75. When β equals zero, the number of available refuelling stations plays no role in the consumers' decision to adopt the new technology and the GB model reduces to the standard Bass model. The higher the value of β, the more important the availability of sufficient refuelling stations is for consumers.

5.4.2 Results

For each combination of a specific scenario and a value of β, I now can compute the adoption speed and corresponding demand for hydrogen vehicles. From this, the time path of costs and revenues and operating cash flows can be computed. These in turn serve as input for the computation of the net present values for each stage as well as the real option value at the start of the project. The results of this exercise are reported in Table 5-2 to Table 5-5. Each table corresponds to a different value of β. The results for scenario Neutral are identical across β values, as the investment gap equals zero all the time.

I start with the case of $\beta = 0$, where infrastructure availability does not influence adoption speed. Essentially, the GBM model reduces to the basic Bass model and adoption is a function of the parameters p and q only. As a result, all scenarios are equal on the revenue side. However, the different scenarios do differ in the speed at which stations are built and, thus, in the time path of cash outflows. The results are provided in Table 5-2. The first three columns of Table 5-2 contain the net present values for each investment phase in present value terms: phase I is between year 1 and year 4, phase II is between year 5 and year 14, and phase III is between year 15 and year 34. Column 4 sums these NPVs and gives the overall NPV of the project at its start. According to the NPV criterion, a minimum condition for the project to start is a positive NPV. Column 5 has the real option value of the project today.[38] According to the real option criterion, the project is feasible when the call option value today exceeds the initially required net investment. I assume this equals the NPV of Phase I operating cash flows in present value terms. The Project Value in column 6 equals the call option value minus the cash flows (required investment) from phase I. That is, a positive project value implies the option is "in-the-money" and can be exercised to start the project.

A first thing to note from Table 5-2 (the case of $\beta = 0$, where infrastructure availability does not influence adoption speed) is that the NPV analysis results in rejection of the project, regardless of the specific time path of investments. This is a common result for large infrastructure projects as uncertainty about future revenues is large and upfront investment outlays are high. From an NPV perspective, no infrastructure developer will start the current hydrogen project. This is exactly the reason why real option theory provides an attractive alternative in project assessment. Table 5-2 shows that the option criterion only rejects the project in the most risky scenario, Aggressive. The scenarios in which investment starts very slowly do best. This result is not surprising. Since demand (adoption) is insensitive to the availability of infrastructure ($\beta = 0$), aggressively and quickly building many stations in the early years does not pay off. It leads to high costs without compensating revenues. Slow investment in the early years reduces costs in the first phase, as can be seen by comparing the Phase I NPV across scenarios in column 1. It puts the scenarios where investment starts more aggressively at a disadvantage.

Table 5-3 to Table 5-5 have the same design as Table 5-2 and provide information on the role of higher sensitivity of demand to available refuelling stations. In Table 5-3, β rises to 0.25 suggesting consumer demand is somewhat sensitive to the availability of refuelling stations. It remains true that the project would be rejected on the basis of overall NPV, but will be accepted using real option valuation regardless of the specific building design. In terms of project value, the scenarios converge a bit. The two slow scenarios (Cautious and Conservative) now have a substantially lower project value, while the project value for Aggressive increases somewhat. These effects are due to the fact that the faster

[38] As the infrastructure project is a multi-stage investment, I use the N-fold compound option model of Cassimon et al. (2004) to compute the real option values.

building scenarios now benefit on the revenue side from faster adoption compared to the slow building scenarios. However, the impact is insufficient to alter the ranking of the projects substantially. Only Confident and Catch-up change places.

When demand sensitivity rises even more with a β of 0.5, I do see somewhat more of an effect. Table 5-4 shows that with this value of β, the scenarios actually converge considerably in overall performance. Differences both in overall NPV and in Project Value are relatively small. Catch-up actually shows the best performance. In Table 5-5, I provide evidence for the case when demand sensitivity is high ($\beta = 0.75$). Now, Cautious and Conservative make up the rear. Actually, the project is rejected for Cautious and only marginally accepted for Conservative. Since Conservative is the scenario which I derived from the HyWays case, it deserves attention on its own. Interestingly it does quite well when there is low demand responsiveness to the availability of infrastructure, but falls to the bottom of the rankings when demand responsiveness increases.

In this particular setup, the consequences of failing to correctly incorporate the endogeneity of demand in the analysis in terms of inappropriately accepting or rejecting the project at the start are limited. Taking the β=0 scenario as our benchmark, the results show that with relatively strong demand responsiveness, Aggressive may be incorrectly rejected, while Cautious may be incorrectly accepted – and even deemed optimal. The project is accepted on the basis of the real option value for all other scenarios for all values of β; however, there is no guarantee decisions would also turn out this way.

Overall, my analysis shows it is important to understand and appropriately model the diffusion process of a new technology like the development of hydrogen-vehicles and the corresponding infrastructure. Ignoring the potential interaction between the speed at which the required infrastructure – and for that matter also a sufficient set of attractive vehicles themselves – will become available and the adoption process, may lead to suboptimal decisions with respect to the optimal timing of investment spending as well as with respect to the assessment of the feasibility of the project in general.

Table 5-2: Comparing scenarios for β=0

Scenarios	Net present value				Real option value			
	Phase I	**Phase II**	**Phase III**	**Total**	**Option value**	**Project value**	**Investment decision**	**Rank**
Neutral	-97	-182	152	-128	136	39	Invest	5
Cautious	-24	-53	76	0	169	145	Invest	1
Conservative	-37	-77	91	-23	161	124	Invest	2
Confident	-64	-124	119	-69	149	85	Invest	3
Aggressive	-130	-241	187	-184	128	-2	**Reject**	6
Catch-up	-64	-164	141	-87	148	84	Invest	4

Table 5-3: Comparing scenarios for β=0.25

Scenarios	Net present value				Real option value			
	Phase I	**Phase II**	**Phase III**	**Total**	**Option value**	**Project value**	**Investment decision**	**Rank**
Neutral	-97	-182	152	-128	136	39	Invest	5
Cautious	-22	-43	14	-51	123	101	Invest	1
Conservative	-36	-69	41	-64	125	89	Invest	2
Confident	-63	-119	91	-91	129	66	Invest	4
Aggressive	-131	-247	211	-166	145	14	Invest	6
Catch-up	-63	-159	121	-102	133	70	Invest	3

Table 5-4: Comparing scenarios for β=0.5

Scenarios	Net present value				Real option value			
	Phase I	Phase II	Phase III	Total	Option value	Project value	Investment decision	Rank
Neutral	-97	-182	152	-128	136	39	Invest	5
Cautious	-21	-36	-62	-119	69	48	Invest	2
Conservative	-35	-62	-18	-116	83	48	Invest	2
Confident	-62	-114	61	-116	108	46	Invest	4
Aggressive	-131	-253	233	-152	159	28	Invest	6
Catch-up	-62	-155	100	-117	121	59	Invest	1

Table 5-5: Comparing scenarios for β=0.75

Scenarios	Net present value				Real option value			
	Phase I	Phase II	Phase III	Total	Option value	Project value	Investment decision	Rank
Neutral	-97	-182	152	-128	136	39	Invest	2
Cautious	-20	-31	-150	-201	13	-7	**Reject**	6
Conservative	-34	-58	-86	-178	38	4	Invest	5
Confident	-62	-110	28	-144	86	24	Invest	4
Aggressive	-132	-260	251	-142	170	38	Invest	3
Catch-up	-62	-152	79	-134	106	44	Invest	1

5.5 Conclusions

In this chapter, I explicitly incorporate the impact that realized investment in new infrastructure may have on adoption speed in a real options framework for investment decisions, and I analyse the consequences of this interdependence for optimal investment. The issue has the characteristics of a chicken-egg problem: without sufficient infrastructure, consumers will not adopt the new technology; but without (likely) adoption, investors will not build the infrastructure. To address the issue of choosing an optimal investment path when adoption depends on previous investments in the necessary infrastructure, I combine a real option modelling approach with a modified Generalized Bass model for the adoption diffusion process.

As an illustration, I apply the combined model to the case of the introduction of infrastructure investments for hydrogen-cars in the Netherlands. I perform a scenario analysis where I combine six different investment strategies with four different parameterizations of the GBM model. I assume that the number of available re-fuelling stations – relative to a linear trend – is a key driver of the diffusion model that captures the adoption decision. The variation in parameterization captures different degrees of demand sensitivity to existing infrastructure.

My results show that it is important to understand and appropriately model the diffusion process of a new technology like the development of hydrogen-vehicles and the corresponding infrastructure. Ignoring the potential interaction between the speed with which the required infrastructure – and for that matter also a sufficient set of attractive vehicles themselves – will become available and the adoption process may lead to suboptimal decisions with respect to the optimal timing of investment spending as well as with respect to the assessment of the feasibility of the project in general. More research is needed to obtain realistic estimates of the magnitude of the relevant parameters that govern the adoption diffusion process for new technologies. This is left to future research.

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Nederlandse Samenvatting

Waterstof is naar voren gekomen als een mogelijke transportbrandstof voor het op lange termijn aanpakken van duurzame energievoorziening, veiligheid en milieuproblemen. De overgang van energieverbruik op basis van fossiele brandstoffen naar duurzame energieoplossingen is een complex sociaal proces. Het innovatieproces voor elke opkomende technologie zoals waterstofbrandstofceltechnologie wordt meestal gekenmerkt als complex, met hoge R & D kosten en omvat hoge mate van onzekerheden over de toekomst van de technologie en de verspreiding in de markten. Waterstofcellen hebben een groot potentieel op de lange termijn, maar ze worden momenteel omringd door vele onzekerheden. Onzekerheden zijn de redenen waarom de planning zo moeilijk is en waarom vaste plannen niet optimaal zijn. Vaak kan bijvoorbeeld geen enkele effectieve besluitvorming in de eerste fase volledig en accuraat worden gemaakt omdat de kennis over toekomstige omstandigheden niet beschikbaar of ontoereikend is.

Over het algemeen wordt aangenomen dat de overgang naar door waterstof aangedreven transport hoofdzakelijk uitdagingen en onzekerheden uit de markt als wel technische en beleidsaspecten ondervindt. Marktbelemmeringen omvatten het opbouwen van een ondersteunende brandstofinfrastructuur, het creëren van een markt voor nieuwe en onbekende voertuigen, en het realiseren van schaalvoordelen bij de productie van auto's, terwijl een aantrekkelijke selectie van voertuigmodellen voor auto-kopers wordt verschaft. Of potentiële klanten de producten zullen accepteren en of publieke gebruikers, zoals transportbedrijven bereid zijn waterstofvoertuigen aan te schaffen, is nog steeds onbekend. Bovendien is technische onzekerheid ook belangrijk. Het heeft betrekking op de onzekerheid van de technologie en hoe het zal ontwikkelen, van cruciale technologische belemmeringen en mogelijkheden om deze op te lossen. Tenslotte is beleidsonzekerheid ook een cruciale factor. De positie en houding van besluitnemers binnen de overheid en de voorspelbaarheid en consistentie van beleidsmaatregelen zoals subsidies, belastingverplichtingen, wettelijke vereisten en overheidsopdrachten voor voertuigen en energiediensten zijn van cruciaal belang voor de inzet van waterstofbrandstofceltechnologie in de maatschappij. Hoge onzekerheid op dit gebied kan het succes van zo'n grote markttransformatie aanzienlijk verminderen.

Grootschalige infrastructuurprojecten zijn riskant omdat ze enorme onomkeerbare investeringen nodig hebben, een lange planningshorizon hebben en vaak gebruik maken van een niet-standaardtechnologie. Bijgevolg ervaren dergelijke projecten vaak kostenoverschrijdingen of tekortkomingen en onvoorziene moeilijkheden. De bedoelde energieovergang naar duurzamer energieverbruik vergroot daarmee de relevantie van een passend kader voor investeringsanalyse. Reële optieanalyse is een opkomend

kapitaalbegrotingsinstrument, dat projectbeheerders kunnen gebruiken voor de toewijzing van hun middelen in het licht van onzekerheid. Het denken in termen van reële opties optimaliseert de manier waarop beleggers omgaan met onzekerheid. Gewoonlijk minimaliseert goed ontwerp het risico, dat zich richt op het vergroten van de betrouwbaarheid en het maken van de beste beslissingen in risicovolle situaties. De reële optiebenadering vult traditionele modellen aan door de waarde van het wachten met investeren te benadrukken Als gevolg hiervan minimaliseert het de initiële kritieke kosten van een beleggingsproject en biedt het de voorwaarden voor flexibele besluitvorming in de toekomst. Dit is cruciaal voor de investeringen in waterstofinfrastructuur, want zelfs bij een volwassen project of technologie is het nog steeds moeilijk om te voorspellen hoe een overgang precies zal evolueren en of het succesvol wordt geïmplementeerd.
In dit proefschrift wil ik de reële optietheorie toepassen op onzekerheidsmodellen die door potentiële investeerders verbonden zijn aan het overgangsproces naar een waterstofinfrastructuur. Ik zal een verzameling dynamische benaderingen ontwikkelen om meerdere onzekerheden te modelleren en strategieën voor het omgaan met onzekerheden en hun oplossingen opstellen. Mijn doel is investeerders te begeleiden om een reeks optimale besluiten te nemen. In dit proefschrift meet ik verschillende bronnen van onzekerheden en ontwikkel ik verschillende reële optiemodellen om de optimale investeringsstrategie van de ontwikkeling van waterstofinfrastructuur in Nederland te onderzoeken. In de analyse zal ik uitgebreid gebruikmaken van de gefaseerde roadmap HyWays, die is ontwikkeld voor de ontwikkeling van waterstations in 10 Europese landen (Finland, Frankrijk, Duitsland, Griekenland, Italië, Nederland, Noorwegen, Polen, Spanje en het Verenigd Koninkrijk). Mijn casestudies zijnontwikkeld door de Europese HyWays-projecties op de Nederlandse markt terug te schalen, gebaseerd op de bevolking en het aantal kilometers aan wegen.

In hoofdstuk twee draag ik bij aan de literatuur door een knock-out barrièreoptie in het N-dimensionaal samengestelde reële optiemodel op te nemen om rekening te houden met de onmiddellijke stopzetting van het project - een zogenaamde plotselinge dood - in een multi-fase investeringsproject. Ik stel voor om het onvoorziene investeringsfalen in kaart te brengen via de evolutie van de onderliggende waarde van het bedrijf. Zodra men door de barrière gaat, zal dit tot gedeeltelijk of volledig falen leiden. De barrière zal fungeren als een ondergrens voor de onderliggende variatie en een reël optiemodel met barrière zal daarom gebruikt worden om een investeringsmogelijkheid te beschouwen met mogelijk voortijdig falen. Ik zal dit model toepassen op een regionaal geval van waterstof-infrastructuurinvesteringen in Nederland en de barrière verder bepalen door een pessimistisch scenario. In de casestudy gebruik ik verschillende externe bronnen om de parameters in het model in te stellen. Vervolgens bereken ik de projectwaarde voor het waterstofinfrastructuurproject in het geval van een barrière van respectievelijk 50 en 70 procent van de NPV van de projectstroom in de volledige commercialiseringsfase en benchmark het tegen de waardering via een NPV-model en een reëel samengesteld optiemodel zonder barrière. Gevoeligheidsanalyse laat zien dat zowel de positie van de barrière als de geaggregeerde volatiliteit een sterke invloed hebben op de optiewaarde.

In hoofdstuk drie ontwikkel en bespreek ik een brede klasse van activumprijsmodellen onder technische onzekerheid en evalueer hun prestaties verder. Dit hoofdstuk draagt bij aan de literatuur door de robuustheid van de reële optiewaardering onder verschillende stochastische processen te onderzoeken. In het bijzonder is de analyse beperkt tot sprong-diffusiemodellen en geometrische Brownse beweging (GBM) modellen. In de klasse van sprong-diffusiemodellen zoom ik verder in op asymmetrische positieve of negatieve en symmetrische sprongen. In het bijzonder onderzocht ik of het benaderen van asymmetrische en symmetrische sprongprocessen door een vergroot GBM tot aanzienlijke prijsfouten leidt. Beide stochastische modellen worden geprijsd met Europese opties voor een breed scala aan parameters die de sprongprocessen kenmerken. Merk op dat ik bij het empirische testen opnieuw de HyWay pilot case zal gebruiken, zodat ik de relatieve prestatie op een consistente manier kan evalueren.

In hoofdstuk vier breid ik het genormaliseerde N-dimensionale samengestelde-optiemodel uit dat door Cassimon en collega’s (2011) is ontwikkeld en neem verdere bijkomende beleidsonzekerheid op. Naar aanleiding van hun benadering worden de verwachte opbrengsten gebaseerd op de initiële schatting van de potentiële marktgrootte gemodelleerd door een geometrische Brownse beweging (GBM). Daarnaast worden discrete succes-faal-waarschijnlijkheden van het project gebruikt om technisch falen in elke beleggingsfase te reflecteren. Bovendien zijn de posities en attitudes van beleidsmakers cruciaal voor de inzet van waterstofbrandstofceltechnologie in de samenleving. Beleidsonzekerheid zal de nadruk krijgen in dit hoofdstuk, waarbij de eigenschappen worden gemodelleerd via een Poisson-sprongproces, dat wordt toegevoegd aan de sequentiële samengestelde optie. Dit model zal worden gebruikt om de risico's van onzekerheid in het klimaatveranderingsbeleid te evalueren, namelijk de stabiliteit van het beleid en de impact van verschillende vormen van beleidsveranderingen. Met zo'n ultieme visie doe ik aanbevelingen aan investeerders over hoe zij beleidsonzekerheid zouden moeten zien, en aan beleidsmakers hoe het beleid zou kunnen worden geïmplementeerd om dergelijke risico's die bij de investering verbonden zijn, te verminderen.

De introductie van een alternatieve transportbrandstof draagt altijd een uitdaging met zich mee die vaak wordt aangeduid als een "kip en ei" probleem. Terwijl consumenten alleen geïnteresseerd zullen zijn in en beginnen met het overschakelen naar een nieuwe brandstof als er voldoende tankstations beschikbaar zijn, zal de industrie alleen investeren in de ontwikkeling van brandstofinfrastructuur als de markt voldoende ontwikkeld is en bestaande stations economisch haalbaar zijn. In hoofdstuk vijf ontwikkel ik een reële optiekader dat deze impact van de adoptiesnelheid op de investeringsbeslissing bestudeert en analyseer ik de gevolgen van deze afhankelijkheid voor de optimale investering verder. Hiervoor integreer ik het N-dimensionele reële optiemodel met een Generalized Bassmodel dat de snelheid van adoptie berekent als functie van de beschikbare tankstations. Op deze manier vat ik expliciet de impact die gerealiseerde investeringen in nieuwe infrastructuur kunnen hebben op adoptiesnelheid in het kader van een reële optie voor investeringsbeslissingen. In deze applicatie ontwikkel ik het diffusieproces zodanig dat het de toekomstige vraag modelleert als functie van het aantal beschikbare tankstations. Ik voer een scenario analyse uit waarbij ik zes verschillende infrastructuurinvesteringsstrategieën combineer met vier verschillende parameterisaties van het model. De variatie in parameterisatie raakt verschillende graden van vraaggevoeligheid voor bestaande infrastructuur. Dit exploratieonderzoek zal de aandacht vestigen op de manier waarop de optimale investeringsweg afhangt van de gevoeligheid van de vraag naar de beschikbare infrastructuur en het daaruit voortvloeiende proces van marktpenetratie en het zal richting geven aan beleggers en beleidsmakers.

Appendix A - Belonging to Chapter 2

A.1. Derivation of the Barrier Option

Let W_τ be a standard Brownian motion. If I consider a function $f(x+W_\tau)$, then from Ito's lemma:

$$df(x+W_\tau) = \frac{\partial f(x+W_\tau)}{\partial W_\tau} dW_\tau + \frac{1}{2}\frac{\partial^2 f(x+W_\tau)}{\partial W_\tau^2} d\tau$$

[A-1]

If I integrate this equation with respect to τ then I obtain:

$$f(x+W_\tau) = f(x) + \int_0^\tau \frac{\partial f(x+W_s)}{\partial W_s} dW_s + \frac{1}{2}\int_0^\tau \frac{\partial^2 f(x+W_s)}{\partial W_s^2} ds$$

[A-2]

Take an expectation on each side of the equation. Stochastic integral vanishes due to martingale property, and then I obtain:

$$E[f(x+W_\tau)] = f(x) + \frac{1}{2}\int_0^\tau \frac{\partial^2 E[f(x+W_s)]}{\partial x^2} ds$$

[A-3]

Now I define the function

$$A(\tau, x) = E[f(x+W_\tau)]$$

[A-4]

Differentiating with respect to τ, I see that $A(\tau, x)$ satisfies the diffusion equation

$$\frac{\partial}{\partial \tau} A(\tau, x) = \frac{1}{2}\sigma^2 \frac{\partial^2}{\partial x^2} A(\tau, x)$$

[A-5]

and subject to the initial condition $A(0, x) = f(x)$, for fixed τ, the random variable becomes $W_\tau \sim N(0, \sigma\sqrt{\tau})$. I can therefore rewrite the solution [A-4] as $A(\tau, x) = E[f(x+\sigma\sqrt{\tau}Z)]$, where Z is a standard $N(0,1)$ random variable.

Explicitly writing out the expectation I have:

$$A(\tau, x) = \frac{1}{\sqrt{2\pi}} \int_{-\infty}^{\infty} f(x + \sigma\sqrt{\tau}\xi) e^{-\frac{1}{2}\xi^2} d\xi$$

[A-6]

Following by the next step, the multi-dimensional Ito rule is a straight-forward generalization of the one-dimensional case. If $C(t,V)$ is the value of a derivative at time t which expires at time T, equation [A-2] must also satisfy the partial differential equation:

$$\frac{\partial C(t,V)}{\partial t} = rC(t,V) - rV\frac{\partial C(t,V)}{\partial V} - \frac{1}{2}\tilde{\sigma}^2 V^2 \frac{\partial^2 C(t,V)}{\partial V^2}$$

[A-7]

Now in order to reduce the above PDE to the diffusion equation, I will make a series of sophisticated transformations. Set $C(t,V) = \alpha(\tau,V)$, where $\tau = T - t$ is a new time coordinate that still runs over the same interval $[0,T]$ as t, but in the opposite direction. I need to reverse the direction of time, so that the terminal payout of the option becomes the initial condition for the diffusion equation. The time derivatives of $C(t,V)$ and $\alpha(\tau,V)$ are related by

$$\frac{\partial C}{\partial t} = -\frac{\partial \alpha}{\partial \tau}$$

[A-8]

while all the other derivatives remain the same. Hence the

$$\frac{\partial \alpha}{\partial \tau} = \frac{1}{2}\tilde{\sigma}^2 V^2 \frac{\partial^2 \alpha}{\partial V^2} - r\alpha + rV\frac{\partial \alpha}{\partial V}$$

[A-9]

This equation now has the “right” sign for the time derivative, and has the initial condition

$$\alpha(0,V_T) = C(T,V_T)$$

$$= F(T,V_T)$$

[A-10]

I now want to eliminate the $r\alpha$ term. I can do this by introducing a “discount factor” $e^{-r\tau}$ explicitly into the equation. Set $\alpha(\tau,V) = \beta(\tau,V)e^{-r\tau}$. The time derivative is then

$$\frac{\partial \alpha}{\partial \tau} = (\frac{\partial \beta}{\partial \tau} - r\beta)e^{-r\tau}$$

[A-11]

and hence Equation [A-11] can be written as

$$\frac{\partial\beta}{\partial\tau} = \frac{1}{2}\tilde{\sigma}^2 V^2 \frac{\partial^2\beta}{\partial V^2} + rV\frac{\partial\beta}{\partial V} \qquad \text{[A-12]}$$

To proceed further, I want to write the equation in terms of the operator $V\partial/\partial V$. This can be easily accomplished by rearranging the second order term,

$$\frac{\partial\beta}{\partial\tau} = \frac{1}{2}\tilde{\sigma}^2 V \frac{\partial}{\partial V}(V\frac{\partial\beta}{\partial V}) + (r - \frac{1}{2}\tilde{\sigma}^2)V\frac{\partial\beta}{\partial V} \qquad \text{[A-13]}$$

I can simplify the operator $V\partial/\partial V$ by defining the new variable $Y = \ln V$, and noting that

$$V\frac{\partial}{\partial V} = \frac{\partial}{\partial Y} \qquad \text{[A-14]}$$

If I then introduce the new function $\gamma(\tau, Y) = \beta(\tau, V)$, I see that the differential Equation [A-13] becomes

$$\frac{\partial\gamma}{\partial\tau} = \frac{1}{2}\tilde{\sigma}^2 \frac{\partial^2\gamma}{\partial Y^2} + (r - \frac{1}{2}\tilde{\sigma}^2)\frac{\partial\gamma}{\partial Y} \qquad \text{[A-15]}$$

Define $X = Y + (r - \frac{1}{2}\tilde{\sigma}^2)\tau$, and set $A(\tau, X) = \gamma(\tau, Y)$. The partial derivative of γ with respect to τ is then given by

$$\frac{\partial\gamma}{\partial\tau} = \frac{\partial A}{\partial\tau} + \frac{\partial A}{\partial X}\frac{\partial X}{\partial\tau} \qquad \text{[A-16]}$$

$$= \frac{\partial A}{\partial\tau} + \frac{\partial A}{\partial X}(r - \frac{1}{2}\tilde{\sigma}^2) \qquad \text{[A-17]}$$

In this way, I obtain the diffusion equation identical to Equation [A-5]

Now I would like to solve the option price $C(t, V_t)$ subject to the terminal condition

$$C(T, V_T) = F(V_T) \qquad \text{[A-18]}$$

where $F(V_T)$ is a prescribed function, that is, the payoff function of the derivative. As noted earlier, $t = T$ corresponds to $\tau = 0$, which is why the terminal payoff function of the derivative is actually an initial condition for $A(\tau, x)$. If I follow through the various transformations made above, then I see that the relation between $C(t, V_t)$ and $A(\tau, x)$ is

$$C(T,V_T) = \alpha(T-t,V_t) \quad [A\text{-}19]$$

$$= \beta(T-t,V_t)e^{-r(T-t)} \quad [A\text{-}20]$$

$$= \gamma(T-t,\log V_t)e^{-r(T-t)} \quad [A\text{-}21]$$

$$= A(T-t,\log V_t + [r-\frac{\sigma^2}{2}][T-t])e^{-r(T-t)} \quad [A\text{-}22]$$

In particular the derivative payoff function can be written as

$$F(V_T) = C(T,V_T) \quad [A\text{-}23]$$

$$= A(0,\log V_T) \quad [A\text{-}24]$$

Hence the initial condition on $A(\tau,x)$ at $\tau = 0$ is

$$A(0,x) = F(e^x) \quad [A\text{-}25]$$

Without the barrier, a call option has

$$A(0,x) = \max(0,e^x - I) \quad [A\text{-}26]$$

Applied Equation [A-6] for the solution of the diffusion equation with the initial condition $A(0,x) = F(e^x)$,

$$A(\tau,x) = \frac{1}{\sqrt{2\pi}}\int_{-\infty}^{\infty} F(e^{x+\sigma\sqrt{\tau}\xi})e^{-\frac{1}{2}\xi^2}d\xi \quad [A\text{-}27]$$

Using this value of $A(\tau,x)$ and the transformation [A-22] I can then write the option price as

$$C'(t,V) = A(T-t,\log V_t + [r-\frac{\sigma^2}{2}][T-t])e^{-r(T-t)} \quad [A\text{-}28]$$

$$= \frac{e^{-r(T-t)}}{\sqrt{2\pi}}\int_{-\infty}^{\infty} F(V_t e^{r(T-t)+\sigma\sqrt{\tau}\xi-\frac{1}{2}\sigma^2\tau})e^{-\frac{1}{2}\xi^2}d\xi \quad [A\text{-}29]$$

Taking into the down-and-out barrier B, the payoff $C'(t,V)$ is zero for all V below the strike I; this translates into for $V<\log(\frac{I}{B})$. I set the barrier below the strike to ensure that $\log(\frac{I}{B})>0$.

Let $V = Be^x$ *and* $k = r / \frac{1}{2}\sigma^2$. *[A-30]*

Barrier option value can be written as $C(t,V) = B \cdot e^{-\frac{1}{2}(k-1)-\frac{1}{4}(k+1)^2\tau} U(t,x)$

In these new variables the barrier transforms to the point $x = 0$, and the barrier option problem becomes

$$\frac{\partial U}{\partial \tau} = \frac{\partial^2 U}{\partial x^2}$$ *[A-31]*

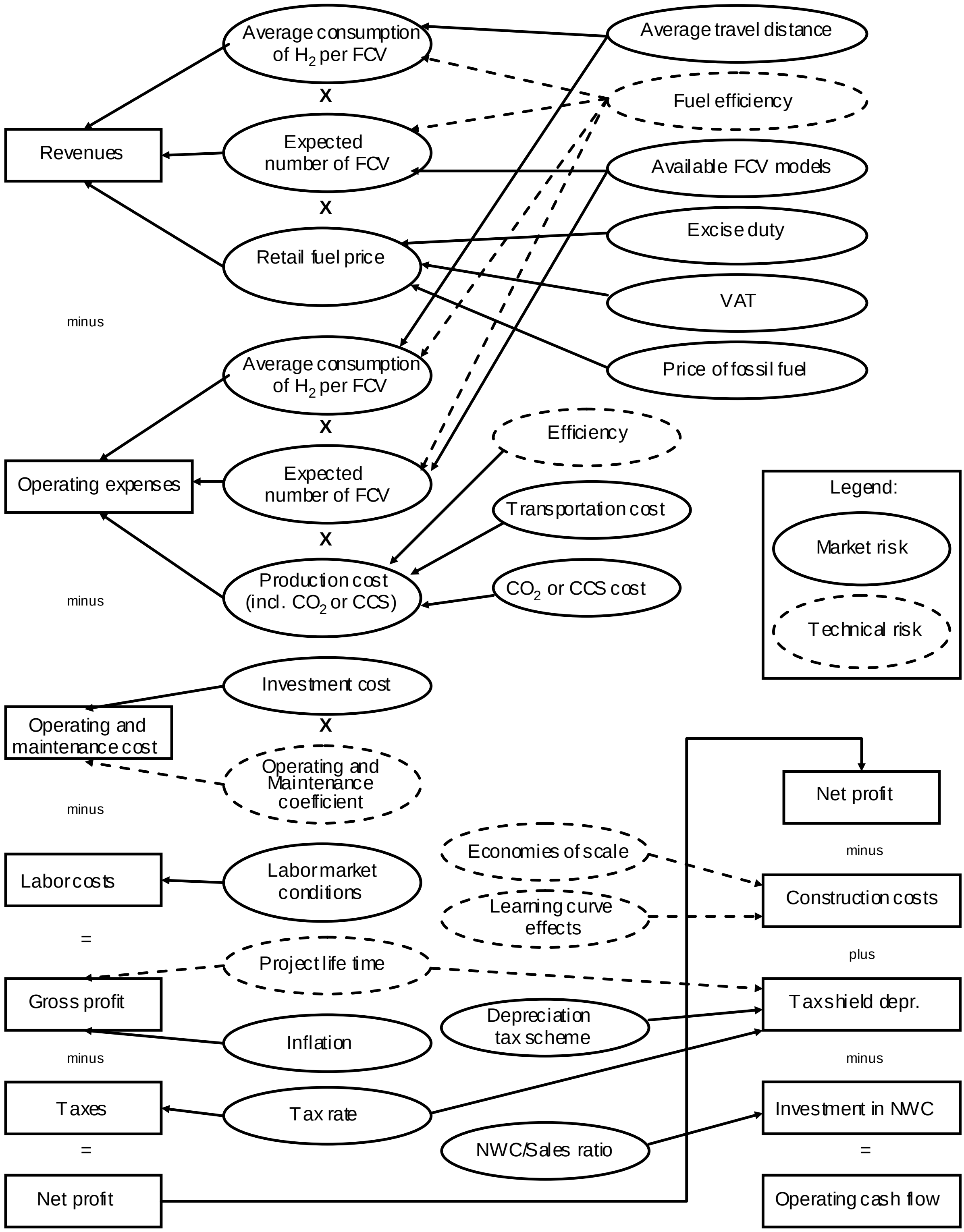
with $U(0,x) = \max(e^{(\frac{1}{2}(k+1)x} - e^{\exp(\frac{1}{2}(k-1)x}, 0), \text{for } x>0$, with $U(0,t) = 0$.

I can now put the pieces together to show that the barrier option value is

$$C(t,V) = VN(d_1) - I \cdot e^{-r(T-t)} N(d_2) - V \cdot (\frac{B}{V})^{k+1} N(d_3) + I \cdot e^{-r(T-t)} (\frac{B}{V})^{k-1} N(d_4)$$ *[A-32]*

which corresponds to Equation [2-9] in the text.

A.2. Structure of the Cash Flow Model



A.3. Company Descriptions of a Set of Comparable Firms

Hydrogenics Corporation designs, develops, and manufactures hydrogen generation products based on water electrolysis technology and fuel cell products based on proton exchange membrane technology in Canada and internationally. The company's OnSite Generation segment develops and sells products for industrial gas, hydrogen fueling, and renewable energy storage markets. This segment's product line comprises HySTAT Hydrogen Stations that provide on-site supply of hydrogen for various hydrogen applications including vehicle fueling, distributed power, and various industrial processes, and provides spare parts and services. Its Power Systems segment develops products for stationary and motive power applications. This segment's product line consists of HyPM fuel cell products, such as HyPM fuel cell power modules, HyPXTM fuel cell power pack, and integrated fuel cell systems, and offers engineering development services. The company serves industrial gas companies, industrial end users, oil and gas companies, and utilities, as well as original equipment manufacturers, systems integrators and end users. It offers its products through direct sales force, as well as through a network of distributors. Hydrogenics Corporation was founded in 1988 and is headquartered in Mississauga, Canada.

Ballard Power Systems Inc. engages in the design, development, manufacture, sale, and service of fuel cell products for motive and stationary power markets primarily in the United States, Canada, the United Kingdom, and Germany. It operates in three segments: Fuel Cell Products, Contract Automotive, and Material Products. The Fuel Cell Products segment provides fuel cell products and services for material handling and bus, back-up power, supplemental power, and distributed generation applications. The Contract Automotive segment provides contract technical and manufacturing, testing, and other engineering services. The Material Products segment provides carbon fibre material products principally for automotive applications and gas diffusion layer material for fuel cell products. Ballard Power has strategic partnerships with Dantherm Power A/S, which develops clean energy backup power through utilization of the company's hydrogen fuel cell technology; and Automotive Fuel Cell Cooperation Corp. that develops fuel cell products for the automotive fuel cell market. The company was founded in 1979 and is headquartered in Burnaby, Canada.

FuelCell Energy, Inc., together with its subsidiaries, engages in the development, manufacturing and sale of high temperature fuel cells for clean electric power generation primarily in South Korea, the United States, Germany, Canada and Japan. The company offers proprietary carbonate Direct FuelCell Power Plants that electrochemically produce electricity from hydrocarbon fuels, such as natural gas and biogas. Its fuel cells operate on a range of hydrocarbon fuels, including natural gas, renewable biogas, propane, methanol, coal gas, and coal mine methane. The company also develops carbonate fuel cells, planar solid oxide fuel cell technology and other fuel cell technologies. It provides its products to universities; manufacturers; mission critical institutions, such as correction facilities and government installations; hotels; and natural gas letdown stations, as well as to customers who use renewable biogas for fuel, including municipal water treatment facilities, breweries, and food processors. The company was founded in 1969 and is headquartered in Danbury, Connecticut.

Plug Power Inc., an alternative energy technology provider, involves in the design, development, commercialization, and manufacture of fuel cell systems for the industrial off-road markets and stationary power markets worldwide. It develops and sells a range of fuel cell systems comprising hydrogen-fuelled Proton Exchange Membrane (PEM) systems. The company's product line includes PEM GenDrive power unit for sale on commercial terms for industrial off-road consisting of forklift or material handling applications, with a focus on multi-shift high volume manufacturing and high throughput distribution sites. It sells its products to business, industrial and government customers through direct product sales force, original equipment manufacturers, and their dealer networks. The company was founded in 1997 and is headquartered in Latham, New York.

Source: Yahoo! Finance (2011)

Appendix B - Belonging to Chapter 4

In order to determine the compound option value, I consider inductively a sequence of call options, with value $\bar{C}_{k+1}(\bar{V}, t)$ which denotes the value of a European call option or 1-fold compound option. $\bar{C}_k$ denotes the 2-fold compound option with exercise price I_k and expiration date T_k, with $T_1 \leq T_2 \leq \cdots \leq T_{k+1}$, and their underlying instruments are the previous call options $\bar{C}_{k+1}$ in the sequence. The following PIDE (Partial Integro-differential Equation) holds for $\bar{C}_k$:

$$\frac{\partial \bar{C}_k}{\partial t} = r\bar{C}_k - \left(r - \delta - \sum_{j=1}^{J} \lambda_j E[\gamma_j - 1]\right)\bar{V}\frac{\partial \bar{C}_k}{\partial V} - \frac{1}{2}\sigma^2\bar{V}^2\frac{\partial^2 \bar{C}_k}{\partial V^2} - \sum_{j=1}^{J} \lambda_j\, E\left[\bar{C}_k\left(\bar{V}q_j, t\right) - \bar{C}_k(\bar{V}, t)\right]$$

[B-1]

with boundary condition:

$$\bar{C}_k(\bar{C}_{k+1}(\bar{V}, T_k), T_k) = p_k max[\,\bar{C}_{k+1}(\bar{V}, T_k) - I_k, 0]$$ *[B-2]*

I would like to determine the value of investment opportunity $\bar{C}_k(\bar{C}_{k+1}(\bar{V}, T_k), T_k)$ at each stage T_k, with boundary condition $\bar{V}_k^*$ as the value of $\bar{V}$ such that $\bar{C}_{k+1}(\bar{V}, T_k) = I_k$ and $\bar{V}_{k+1}^* = I_{k+1}$.

Note that $\bar{C}_k(\bar{V}, T_k)$ stands for the price of the underlying compound option. Conditioning on the number of jumps gives:

$$E\left[max\left(\bar{V} - I_1, 0\middle|(n_1, \ldots, n_J\right)\, jumps\right] = \bar{V}(0)\, exp\left[(r-\delta)\, T_1 + \sum_{j=1}^{J} n_j\beta_j + \sum_{j=1}^{J} n_j\sigma_j^2\right] N_1(\bar{a}_1) - I_1 e^{-rT_1} N_1\left(\bar{b}_1\right)$$ *[B-3]*

where

$$\bar{a}_1 = \frac{ln\frac{\bar{V}}{I_1} + (r-\delta)T_1 + \frac{1}{2}\sigma^2 T_1 + \sum_{j=1}^{J} n_j\beta_j + \sum_{j=1}^{J} n_j\sigma_j^2}{\sqrt{\sigma^2 T_1 + \sum_{j=1}^{J} n_j\sigma_j^2 + \sum_{j=1}^{J} n_j\beta_j}},$$

$$\bar{b}_1 = \bar{a}_1 - \sqrt{\sigma^2 T_1 + \sum_{j=1}^{J} n_j\,\sigma_j^2 + \sum_{j=1}^{J} n_j\beta_j}$$

Summation is over the J classes of discrete events and therefore the actual drift of the stochastic process becomes $r - \delta - \sum_{j=1}^{J} n_j\beta_j - \sum_{j=1}^{J} n_j\sigma_j^2$.

Second, since the joint probability of the random realization of $n = (n_1, \ldots, n_J)$ jumps is $\prod_{j=1}^{J}[\frac{e^{-\lambda_j T_1}(\lambda_j T_1)^{n_j}}{n_j!}]$, I have the following unconditional formula:

$$\bar{C}_1(\bar{V},0) = p_1 e^{-rT_1} \sum_{n_1=0}^{\infty} \cdots \sum_{n_J=0}^{\infty} \left\{ \prod_{j=1}^{J} [\frac{e^{-\lambda_j T_1}(\lambda_j T_1)^{n_j}}{n_j!}] E[max[\bar{V} - I_1, 0]|t] \right\}$$

$$= p_1 e^{-rT_1} \sum_{n_1=0}^{\infty} \cdots \sum_{n_J=0}^{\infty} \left\{ \prod_{j=1}^{J} [\frac{e^{-\lambda_j T_1}(\lambda_j T_1)^{n_j}}{n_j!}] [\bar{V}(0)\, exp[(r-\delta)\, T_1 + \sum_{j=1}^{J} n_j\, \gamma_j]\, N_1(\bar{a}_1) - I_1 e^{-rT_1} N_1(\bar{b}_1)] \right\}$$

Going to the compounding (i.e. k $\neq 0$, t $\neq 0$), I have:

$$\bar{C}_1(\bar{V},0) = h_{k+1} \prod_{p=1}^{k+1} \{ \sum_{n_{p_1}, n_{p_2}, \ldots, n_{p_J}=0}^{\infty} \prod_{j=1}^{J} [\frac{e^{-\lambda_j \tau_p}(\lambda_j \tau_p)^{n_{p_j}}}{n_{p_j}!}]\, \bar{V}(0)\, exp(-\delta_{s_{k+1}} T_{k+1})\, N_{k+1}(\bar{a}_{s_1}, \bar{a}_{s_2}, \ldots, \bar{a}_{s_{k+1}};\, \Xi_{k+1}) \} - $$
$$- \sum_{i=1}^{k+1} \{ \prod_{p=1}^{i} [\sum_{n_{p_1}, n_{p_2}, \ldots, n_{p_J}=0}^{\infty} \prod_{j=1}^{J} [\frac{e^{-\lambda_j \tau_p}(\lambda_j \tau_p)^{n_{p_j}}}{n_{p_j}!}]\, h_i I_i e^{-rT_i} N_i(\bar{b}_{s_1}, \bar{b}_{s_2}, \ldots, \bar{b}_{s_i};\, \Xi_i)]\},$$

where

$$\delta_{s_p} = -\frac{\beta_{\gamma_p} + \frac{1}{2}\sigma_{\gamma_p}^2}{T_p} + \delta + \sum_{j=1}^{J} \lambda_j \left(exp\left(\beta_j + \frac{1}{2}\sigma_j^2\right) - 1 \right) =$$

$$= -\frac{\beta_{\gamma_p} + \frac{1}{2}\sigma_{\gamma_p}^2}{T_p} + \delta + \sum_{j=1}^{J} \lambda_j \left(exp\left(\beta_j + \frac{1}{2}\sigma_j^2\right) - 1 \right)$$

$$\sigma_{s_p}^2 = \sigma^2 + \frac{\sigma_{\gamma_p}^2}{T_p},\ p=1,\ldots,i$$

$$\bar{a}_{s_p} = \bar{b}_{s_p} + \sigma_{s_p}\sqrt{T_p};\ \ \bar{b}_{s_p} = \frac{ln\frac{\bar{V}}{\bar{V}_p^*} + \left(r - \delta_{s_p} - \frac{1}{2}\sigma_{s_p}^2\right)T_p}{\sigma_{s_p}\sqrt{T_p}},\ p=1,\ldots,i$$

$$\beta_{\gamma_p} = \sum_{r=1}^{p} \sum_{j=1}^{J} n_{r_j}\beta_j = \sum_{j=1}^{J} \beta_j s_{p_j},\ p=1,\ldots,i$$

$$\sigma_{\gamma_p}^2 = \sum_{r=1}^{p} \sum_{j=1}^{J} n_{r_j}\sigma_j^2 = \sum_{j=1}^{J} \sigma_j^2 s_{p_j},\ p=1,\ldots,i$$

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