2

Literature Review

As indicated in the preceding chapter, our research builds on concepts that have been developed in previously unlinked areas. We therefore have to draw on different strands of literature that can be subsumed under the following categories: new product development, decision models with information updating, and real options theory.

This chapter surveys these literature strands and reviews the relevant concepts and theories. We start with the literature on new product development, providing an overview of key development project characteristics as well as the success factors identified by empirical studies. Thereafter, decision models with information updating possibilities are reviewed. Besides giving an overview of the relevant information updating modeling approaches, we study corresponding decision frameworks developed in different areas of operations management and discuss their applicability to our research objective. Finally, the key concepts of real options theory are presented, including different valuation methods and insightful frameworks for research and development applications.

2.1 New Product Development

This section presents the key characteristics of new product development projects and reviews the (empirical) literature with respect to identified challenges as well as success factors of managing the project inherent uncertainty. The literature on this topic is vast since it encompasses marketing, engineering, strategic, as well as organizational and behavioral aspects. Given our research objective, we will thus primarily focus on uncertainty reduction and information generation related approaches from an operations

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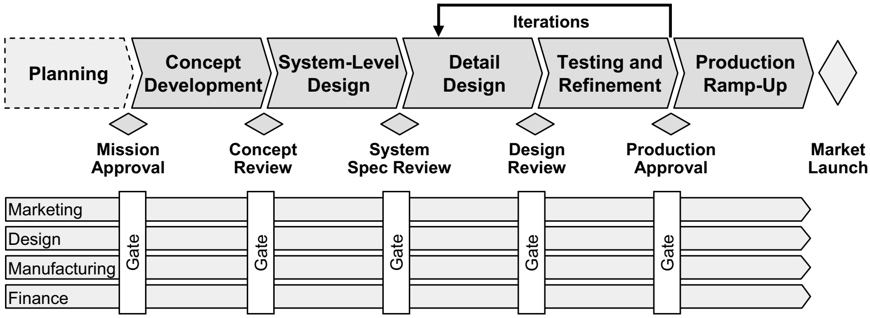


Source: Adapted from Ulrich and Eppinger (2004).

Fig. 2.1. Stage-gate development process

management perspective.[1] The obtained insights will highlight the need for quantitative decision models in order to enhance the understanding and the management of uncertainty in the area of NPD. In addition, they will illustrate the basic characteristics of NPD projects underlying our framework.

2.1.1 NPD Process Characteristics

The development of a new product generally comprises all activities starting with the identification of a market opportunity and ending with the launch of the product into the market. It is therefore more specific and targeted than general research activities (cf. e.g., Brockhoff 1997a, p. 35 ff.). The generic process of NPD is a sequential approach driven by the chronological progression of development tasks. The first formal schemes, today often referred to as the phased review process, elaborate on the physical sequence and brake up the development activities in discrete phases, each ending with a review point where decisions about the further progression and its funding are made (Cooper 1994). Thus, this formal process has almost solely a project management focus on the engineering activities in order to ensure the completion of the project on time, within specification and budget. It further addresses only technical risks and ignores relevant tasks in marketing or finance as well as any interactions between these different functional disciplines.

These deficiencies have been addressed in the so-called stage-gate process models (Fig. 2.1). Resembling somewhat the phased review process,

[1]For a more general overview of the product development literature, the interested reader is referred to excellent reviews of Krishnan and Ulrich (2001) (decision making), Griffin and Hauser (1996) (marketing aspects), Brown and Eisenhardt (1995) (organizational perspective), Montoya-Weiss and Calantone (1994) (environmental and contextual variables), or Ernst (2002) (general success factors).

they also break the NPD process up into a predetermined set of stages with predefined checkpoints (gates). The difference to the previous models is that each stage comprises clearly prescribed cross-functional and parallel activities. The gates after each stage contain deliverables for each functional area that the project must pass in order to proceed to the next stage. Typically, between four to six stages are found in industry (Cooper 1994). The first stage, planning, builds upon advanced research and development activities by investigating the market potential of the product concept, exploring possible product architectures and manufacturing methods, as well as conducting financial studies. The results of these analyses build the basis for the business case of the project which sets the aimed project specifications, defines the required tasks, and describes the budget and schedule constraints. After the formal approval of the project, these aspects are refined and further explored during the concept development stage before the actual design activities are started (system-level design phase). Over several building, testing, and reworking iteration cycles, the product advances, reaches manufacturability, and finally, during the production ramp-up stage, the readiness to be launched into the market.

By integrating all involved departments into the development process, the stage-gate model is highly cross-functional, has a strong market orientation, and fosters a holistic assessment of the NPD project over the entire process. Besides technical aspects, management is thus urged to also assess market, financial, and legal aspects of the projects on an ongoing basis. In addition, with precisely defined deliverables and clear go/no-go decision criteria at each gate, this approach encourages task completion and decision making. It thus builds the basis to deal effectively with market and technology uncertainty surrounding NPD projects (Lint and Pennings 2001; Griffin and Hauser 1996).

To further increase the efficiency of the stage-gate process, several refinements of this approach have been proposed focusing on speed, flexibility, and more efficient allocation of development resources. Takeuchi and Nonaka (1986), for example, stress the need for addressing the continuous interactions between the members of the multidisciplinary team and the parallel processing of tasks in the development process. Their process has therefore overlapping stages where operational decisions are incrementally made within the teams. Strategic decisions of the project, however, are delayed for a more flexible response to market changes. Similarly, Cooper (1994) proposes fluid and overlapping stages to shorten cycle and development times and to account for parallel development efforts like concurrent engineering. In this process, the gates are not fixed anymore, but fuzzy in order to allow for conditional and situational decisions. This avoids, for example, project delays when certain (minor) criteria in a functional area are not met. In other words, the so-called third-generation processes propose higher flexibility to address the project specific development characteristics and to account for the inherent uncertainties. Most companies have integrated such flexibility in different degrees into their conventional stage-gate processes.

But regardless of the degree of flexibility, parallelism, or fuzziness of the activities and gates, the in principle sequential nature of the major tasks and building blocks remains and requires still – if not even more – precise valuation criteria for go/no-go decisions. The development process thus evolved from a pure project management driven description of design activities to an information processing (Levitt et al. 1999; Loch and Terwiesch 1998) and risk managing system (Riek 2001; Büyüközkan and Feyzioglu 2004). From the latter perspective, the process starts with the identification of various risk factors, their evaluation, and prioritization. As the project progresses, however, these risks are generally reduced as uncertainty gradually resolves with technical problems being solved and more information about the market, e.g., customer requirements, sales volume, competitive environment, etc., is becoming available (Ulrich and Eppinger 2004). Thus, information generation and processing is highly linked with managing the project inherent risk.

2.1.2 Types of Uncertainty and Possible Responses

Development projects are exposed to numerous uncertainties. They can generally be traced back to the following sources: market, technical, resource, and schedule uncertainty (cf. e.g., Souder and Moenaert 1992; Huchzermeier and Loch 2001; Ulrich and Eppinger 2004, p. 20 f.). Market and technical uncertainty are often regarded as the most decisive ones while budget and/or schedule overruns are either induced by the former two sources of uncertainty or arise from managerial or organizational deficiencies. In the following, we therefore will solely concentrate on the former. Market uncertainty comprises, for example, customer requirements, moves of competitors, market size, or pricing. Technical uncertainty, on the other hand, relates to aspects like technology selection, design and product architecture, or the definition of product specifications. The overall degree of uncertainty is of course highly project specific and depends on aspects like the degree of innovation, selected technology, project duration, or the characteristics of the target market. Independently thereof, the overall uncertainty is generally highest in the early stages of the development process, often called the fuzzy front end, when the customer requirements and other market characteristics are still too ambiguous and many technical details have not yet been resolved (Dahan and Mendelson 2001; Schröder and Jetter 2003). In presence of such uncertainty, management has to adjust its development efforts accordingly.

Numerous approaches have been developed to respond to these uncertainties with appropriate concepts and frameworks. From a project management perspective, a well-defined and consequently implemented development process facilitates, as indicated above, the management of uncertainty. The precisely described tasks and valuation criteria at the different decision gates ensure that the project only progresses if all necessary issues have been sufficiently addressed. Several empirical studies stress that an implemented, formal development process is a key success factor for NPD projects exposed to (high) uncertainty (e.g., Griffin 1997b; Cooper and Kleinschmidt 1995, 1996). With respect to the uncertainty the project is exposed to, it is essential to adapt the generic development process accordingly to the firm's and the project's unique context and to choose an appropriate development strategy (cf. Ulrich and Eppinger 2004, p. 18. ff.).

Technical uncertainty can be reduced, for example, by exploring multiple solution paths in parallel. It is an expensive, but effective approach to ensure that one of the developed solutions succeeds and is therefore well suited for projects exposed to high technical uncertainty as Srinivasan et al. (1997) show. They provide empirical evidence that parallel prototyping resolves significant uncertainty in the mid to late stages of the NPD process. Dahan and Mendelson (2001) indicate that parallel development is also valuable in the early phases, i.e., to pursue multiple concepts in parallel and select the best design at a later stage. Postponing the finalization of the project specifications may be particularly beneficial in dynamic environments as Bhattacharya et al. (1998) stress. Where such an approach is either not applicable or too costly, an iterative development process with rapid design-build-test cycles may allow to resolve technical uncertainties in a fast and efficient manner (Thomke 1998; Smith and Eppinger 1997). Besides adapting the development approach to the technical problem setting, the project itself can be adjusted and setup in such a way that the inherent technical uncertainty is already a priori reduced. Decreasing the complexity by reducing the number of new parts or the diversity of applied core technologies lowers the technical development uncertainty and hence, increases the project success rate as Murmann (1994) as well as Meyer and Utterback (1995) empirically demonstrate.

Market uncertainty, on the other hand, can on a conceptual basis be reduced by shortening development lead time (Shelley and Wheeler 1991). A prominent approach therefore is the already mentioned parallelization of development tasks through implementation of concurrent or simultaneous engineering (Krishnan et al. 1997). With the reduced time span between the start of the development activities and the market launch when most of the uncertainty is resolved, a shorter time horizon has to be overlooked and hence, certain trends may already be observable at this project stages. A high development flexibility to address late market requirement changes and to postpone the final specification of the product is another approach to respond to uncertainty stemming from the market side. This can be achieved, for example, through a modular product architecture (Ulrich 1995; Krishnan and Bhattacharya 2002).

In case of extremely high uncertainty in NPD projects, so-called unforeseeable uncertainty, which prevents to recognize the relevant influence variables and hence, to plan ahead of time, the only two fundamental strategies are trial and error learning and selectionism (Pich et al. 2002). The former strategy tries to flexibly adjust project activities to new information as it becomes available at the costs of failures and project delays. Selectionism, on the other hand, involves pursuing several approaches in parallel and independently of one another and selecting the best one ex post. The costs of this strategy are also very high due to parallel activities (including bound resources) as well as forgone profits due to elimination of product variants. Sommer and Loch (2004) show that in presence of unforeseeable uncertainty and poor testing possibilities, trial and error learning should be preferred over selectionism. In case of perfect testing opportunities, both strategies offer equal results.

The extremely high costs of both approaches limit their practical applicability on NPD cases where uncertainty is completely unforeseeable. As stated before, such an uncertainty holds only true for a diminishing number of NPD projects. In most other cases, however, the influenceable variables and their functional relationship are known. Thus, less expensive approaches can be applied to reduce uncertainty. For these projects, which are also in the focus of our model, the timely generation and integration of information during the development process remains key to optimal decision making.

2.1.3 Information Generation and Updating

Numerous empirical studies stress the importance of timely identifying and evaluating external trends in order to update and revise current project targets during the development process. Atuahene-Gima (1995) and Mishra et al. (1996), for example, show that the generation of market information about current and future customer needs, competitive dynamics, and technology changes throughout the development process (and product life cycle) has a high impact on the future project success. These insights are supported by Balbontin et al. (1999), who study new product development success factors in American and British firms. In addition to the former two studies, they observe a high correlation between a company's forecasting activities and abilities (e.g., of the market potential and volume) and the NPD success. Finally, the findings of Cooper and Kleinschmidt (1994) stress the importance of observing the competitive environment in order to reduce this kind of market uncertainty and hence, to timely respond to competitors' moves by adjusting project targets. On the other hand, there are several large scale numerical studies who identified inadequate market analysis as well as lack of appropriate market data and updates among the top three factors for NPD project failures (cf. e.g., Cooper and Kleinschmidt 1996; Little 2004).

On the technical side, the feasibility of the selected product concept and architecture (Carbonell-Foulquié et al. 2004; Polk et al. 1996) as well as information about the development of the underlying technology (Iansiti 1995), especially for novel products, are regarded key to resolve technical uncertainty. Moreover, Loch and Terwiesch (1998) analytically show that this type of uncertainty, causing costly engineering changes, can be reduced through the continuous exchange of current design solutions between the involved development teams. The challenge is to find the optimum between the number of exchanges to reduce the negative effect of rework and the expense for the communication time. Only if concurrency and communication are simultaneously considered, the highest possible uncertainty reduction and hence, the optimal time-to-market is achieved.

The optimal method for generating such information during the NPD process depends on the development stage as well as on the type and degree of uncertainty. In the following, we will briefly survey the most important models and review the limited number of empirical studies that examine their respective effectiveness. As we will model the update of market requirement information in our decision framework, the focus will primarily be on methods reducing the market uncertainty. However, approaches to reduce other sources of uncertainty, in particular technical uncertainty, cannot independently be treated of each other and will therefore be sketched first.

In the early phase of the development process, uncertainty regarding the feasibility of certain technical solutions can be reduced by increasing the application of simulation and other virtual development techniques, e.g., digital mock up (DMU). Dahan and Srinivasan (2000) show that virtual prototypes are nearly as effective for concept selection and testing as physical ones. Where the latter are required, one can use rapid prototyping instead in order to obtain a physical prototype from computer models. This concept has proven to be an effective means to embody product concepts quickly and inexpensively, which enhances technical problem solving during the early development stages (Wall et al. 1992). The optimal prototyping and testing strategy as well as the optimal switch from virtual to physical modes depends on the inherent uncertainty and the cost of redesign (Thomke 1998; Thomke and Bell 2001).

Such prototypes are also very valuable for communicating product concepts to potential customers at an early stage. Especially for very innovative products, early feedback is crucial for product success. The integration of so-called lead users is therefore valuable (cf. e.g., von Hippel 1986; Albach 1993, p. 275 ff.). Since these customers expect great benefits from the developed product, they are willing to support the development process by bringing in their knowledge and experience or by testing early prototypes. The value of the obtained information depends on the degree and the point in time of their involvement as well as the respective incentives for them. With respect to time, lead user integration seems to be most valuable during the early stages for the evaluation of product concepts as well as during the testing phase (Gruner and Homburg 2000). During the design phase, the involvement often causes disturbances and bears the risk of addressing the specific lead user needs too much, thus drifting towards a niche market solution (Brockhoff 1997b).

The most common means of market information generation are, however, the traditional market research methods (Lynn et al. 1999; Zahay et al. 2004). Besides still prevailing simple customer surveys, multi-attribute models like conjoint analysis are the most popular methods for the identification of customer requirements prior to the start of the development project. The latter methods are used to determine the relative importance of certain product features by asking customers to evaluate alternative product concepts characterized by a set of attributes. The obtained data allows to estimate the potential market share of each concept in this set of alternatives and to derive an optimal product concept. In a similar way, quality function deployment (QFD) links customer needs to design attributes (cf. e.g., Griffin and Hauser 1993; Brockhoff 1999, p. 178 ff.). This method differs from the simple comparison of concept alternatives based on multi-attribute insights. QFD particularly fosters the interaction between marketing and engineering during the process of converting customer needs into engineering solutions. Thus, it also has an organizational impact.

The problem of either method is that the customer requirements are surveyed prior to the start of development activities and that they are generally not updated (von Hippel 1992). Thus, problems arise if the needs change. This is especially the case in highly dynamic environments (Bhattacharya et al. 1998). In addition, customers often do not know themselves which products they will need at the moment of the market launch. Although these are known problems, hardly any study exists measuring the accuracy of such market studies or the reliability of the applied methods. Among the few, Mahajan and Wind (1992) empirically study the usage and satisfaction of frequently applied market research methods in NPD projects. They report inaccuracy (e.g., of QFD, focus groups, and life cycle models) and inability to capture the market complexity (e.g., of conjoint analysis or focus groups) as the major shortcomings of these models. Based on a sample of 168 firms, Kahn (2002) reports an average accuracy for market and customer forecasts of about 58% over an average forecast time horizon of 26 month.[2] For products with a higher degree of innovation, the forecast accuracy is even lower, i.e., 47% for new-to-the-company and 40% for new-to-the-world products.

Other forecast accuracy studies with a particular focus on NPD projects seem only to exist for sales and profit forecasts. However, these studies are rare and partly outdated (Gartner and Thomas 1993). Tull (1967) as well as Tull and Rutemiller (1968), for example, compare the actual and predicted sales for new products based on a sample of 53 products from 16 firms. They report high inaccuracy for sales as well as profit forecasts with an average mean error of 65% and 128%, respectively. Beardsley and Mansfield (1978) also find a relatively low correlation of 0.37 between initially forecasted and actual profits of 57 product and process innovations of a single firm. Finally, Shelley and Wheeler (1991) report an average ratio between actual and forecasted sales of 79% in the first year which continuously decreases to 41% in the fifth year.

Although these studies measure only the accuracy of sales forecasts made at the moment of the product launch, the accuracy of forecasts made prior to the start of the project or during the development process might be even worse. Together with the findings reported above, these studies clearly indicate the need for regular updates in order to reduce market uncertainty for optimal decisions during the development process. A positive impact of information updates on NPD success has also been empirically validated (cf. e.g., Rothwell et al. 1974; Balbontin et al. 1999). Despite these insights, the number of corresponding models is limited and has not been of major interest in disciplines like management science or operations management (cf. e.g., Wind and Mahajan 1997; Krishnan and Loch 2005). The development of more formal and quantitative models in order to improve the resolution of uncertainty and to enhance decision making especially during the early stages is therefore a frequent request of researchers in this field (Mahajan and Wind 1992; Gerwin and Susman 1996). We will thus review the existing information updating and valuation approaches and evaluate their applicability to this problem in the next sections.

2.2 Decision Models with Information Updating

Researchers in various disciplines have developed decision models that deal with information updating. In the following, we will provide a brief overview of information updating within the decision theory before surveying the most interesting models related to our research objective. Since

[2] Unfortunately, the term "forecast accuracy" is not precisely defined in this article. It is only stated that the participating firms were asked to indicate the degree of forecast accuracy one year after the product launch.

information updating has hardly been addressed in the area of NPD, we will study similar decision frameworks from related disciplines, like supply chain management for example, and present the most relevant updating approaches. The focus of the latter aspect will primarily be on statistical decision theory, in particular Bayesian analysis, which we will apply to our valuation model. Finally, some decision models in the field of NPD that incorporate information updating will be analyzed in greater detail.

2.2.1 Foundations of Decision Theory and Information Updating

Decision theory is the study of decision making involving and being of interest to researches in many different disciplines like mathematics, statistics, economics, philosophy, psychology or behavioral science – to name but the most important ones. The vast body of knowledge goes back as far as to the eighteenth-century like to the theory on the measurement of risk by Daniel Bernoulli (1738) or to the notion of probability as a theory of rational degrees of belief developed by Thomas Bayes (1764).[3] The modern decision theory builds up on the work of von Neumann and Morgenstern (1944) and Savage (1954), who provide with the expected utility theory an important foundation of decision making under risk. One part of it – the so-called prescriptive decision theory – is concerned with the derivation of optimal strategies when a decision maker is faced with several decision alternatives and an uncertain or risk-filled pattern of future events (Laux 1991, p. 3 ff.).

An important characteristic of many decision problems of this type is that the decision maker's uncertainty is not constant over time. It rather depends on the point in time when the decision is made. As time progresses and the moment of the uncertainty resolution comes closer, the decision maker is generally less uncertain than he was at times farther away. The reason for the uncertainty reduction is that he can acquire additional information and thus, learn about future states of the world as time goes by (Marschak and Nelson 1962). This property is at the heart of information updating. The additional information is, however, only valuable for the decision maker if he has flexibility to respond to it (Merkhofer 1977). Numerous models for decision making in the presence of managerial flexibility to respond to new information in uncertain environments have been developed. NPD projects are characteristic examples where management has to refine its information over time and adjust its initial decisions.

The basic idea behind these decision models under preliminary information is the following (see also Fig. 2.2): In situations with uncertainty, the decision maker has often prior information about the unknown states of

[3] The latter seminal work builds a cornerstone in the statistical decision theory to which we will refer to in our model formulation. See Section 3.2 for details.

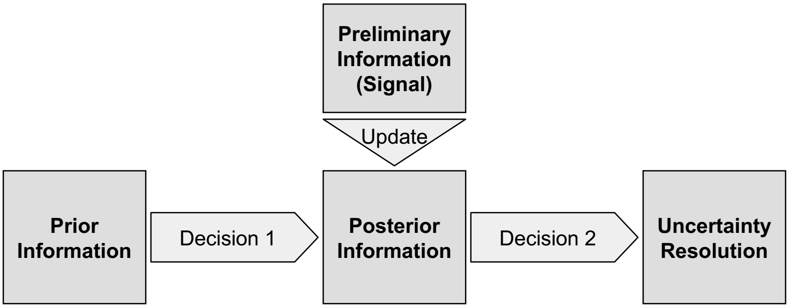


Fig. 2.2. Decision making with information updating

nature. In order to make the best possible decision, however, he may have the flexibility to postpone (part of) the decision until additional information becomes available. This new information can then be used to update the initial (prior) probability estimates about the state of nature so that the final decision is based upon more accurate data. The postponement of some decisions until a later point in time when more information is available generally comes at the expense of higher second stage costs. Late decisions that require fast production modes or design changes close to the market launch incur much higher costs compared to early actions. Thus, a frequent trade-off is to make either an early decision at low cost but with limited information or to postpone it until more information becomes available at the expense of higher cost (Loch and Terwiesch 2005).

Although many decisions in operations management involve this issue, corresponding models have been developed so far primarily in the area of supply chain management where information updating is a prevailing issue.[4] Key decision problems with uncertainty reductions through information or forecast updates in this fields are, for example, optimal inventory replenishing policies (e.g., Johnson and Thompson 1975; Lovejoy 1990), information-sharing mechanisms to reduce variability effects in supply chains like the bullwhip effect[5] (e.g., Lee et al. 2000; Gaur et al. 2005), or optimal ordering and production modes for items with uncertain demand patterns (e.g., Hausman and Peterson 1972; Fisher and Raman 1996; Eppen and Iyer 1997). The challenge underlying these decision problems is

[4]For a systematic overview of the development of dynamic inventory modeling under uncertainty and the corresponding mathematical and statistical methods of it, see, for example, Girlich and Chikan (2001).

[5]The bullwhip effect describes the phenomenon that the sequence of order quantities tends to have a higher variability and a larger order size as one moves upstream the supply chain, i.e., from the retailer to the manufacturer (Lee et al. 1997).

the optimal response to high demand variability. Depending on the studied issue, the demand uncertainty and its reduction is hereby modeled in different ways. Three major updating methods applied to decision models can be distinguished: time series analysis, Markov-modulated forecast updates, and Bayesian analysis (cf. Sethi et al. 2005, p. 8 ff.).[6]

In the following, we will focus on the latter method which is – compared to the former – best suited for the above described decision problem with preliminary information.[7] Since the most popular applications of this updating method are supply chain management decision problems, we have to refer to the models in this area. Although the context differs from the one of NPD projects, the underlying decision problem is identical: Instead of demand uncertainty, management of NPD projects has market uncertainty that can be reduced with new information acquired during the development process. The obtained insights from the supply chain management literature can therefore be applied to our decision problem. However, as the subsequent discussion will show, the applied methodology cannot be transferred in a straightforward manner, but has to be slightly adjusted.

2.2.2 Bayesian Analysis

2.2.2.1 Foundations and Basic Ideas

Bayesian analysis is a popular method in the field of statistical decision theory which is concerned with the problem of making decisions based on statistical knowledge about uncertain quantities. In order to obtain information about critical parameters, the decision maker faces the challenge of designing appropriate studies, analyzing data sets, and fitting probability models. While classical or frequentist statistics uses the sample data from experiments or studies directly in order to make inferences about the unknown parameters, Bayesian statistics[8] combines this data with other relevant information about the problem. This so-called prior information primarily arises from other sources than statistical investigation, like past project experience, for example. By combining the prior information about the states of nature of the decision problem with the additional information obtained

[6] These very general forecasting methods are also known in the literature as the state space forecasting approach (cf. e.g., Abraham and Ledolter 1983, p. 359 ff.).

[7] For the characteristics and shortcomings of time series analysis see e.g., Veinott (1965), Kahn (1987), or Lee et al. (2000) and of Markov-modulated forecast updates see e.g., Chen and Song (2001), Sethi et al. (2005), or Karr (1991).

[8] Named after Thomas Bayes, a minister and amateur mathematician, who set down his findings on probability in an "Essay Towards Solving a Problem in the Doctrine of Chances", published posthumously in the Philosophical Transactions of the Royal Society of London (Bayes 1764).

from (market) research or experimentation, the posterior distribution, i.e., the conditional distribution of the unknown quantities given the additional data, can be computed. All further inferences are then made from these updated beliefs (cf. e.g., Berger 1985).

In the past, there has been a long and intense controversy between frequentists and Bayesians statisticians regarding the appropriate approach to statistical data analysis and decision making (Berger 1985, p. 124 f.). The former group developed methods based on sampling from a large population which dominated the field for a long time. They criticized the Bayesian methods for their high dependency on correct and robust priors, the often subjective estimates, and their over-reliance on computationally convenient priors. The latter criticism refers to the fact that previously posterior distributions could only conveniently be determined for models where the prior belongs to the same distributional family as the sample data (so-called conjugate families).[9] Bayesians in turn complained that the frequentist approach ignores to incorporate relevant and insightful prior information and that this method requires large samples to derive significant and robust results which is often costly and inefficient.

Most of these controversial issues have been overcome. Computational advances from the mid-1980s on allowed to apply simulation methods, in particular Markov chain Monte Carlo simulations, to determine posterior distributions for a wide class of distributions and models (cf. Rossi et al. 2005, p. 1). Although frequentism remains to be the more robust approach due to its reliance on larger sample data, it is less suited for making decisions on the basis of limited information. More precisely, many classical large sample procedures simply fail if only a small data basis is available. Bayesian procedures with their ability to combine the sample data with prior estimates or beliefs generally provide better results in such situations and hence, would almost always be preferable (cf. Berger 1985, p. 125). The latter aspect is important for many real-life situations where the available data basis is often sparse due to budget or time constraints.

In addition, Bayesian analysis follows the natural way of making decisions in practical situations by starting with subjective estimates about uncertain outcomes of the project which are later revised and updated when new information becomes available. The derived insights and decisions from such an analysis are also more easily interpretable by non specialists.[10] The superiority in many situations explains the dramatic increase in the use of Bayesian methods in the different academic disciplines over the

[9]For details, see Section 3.2.1 or Carlin and Louis (2000, p. 25 ff.).

[10]Besides these benefits, there exist several other advantages Bayesian analysis offers compared to the classical statistical methods for which the interested reader is referred to the excellent textbook of Berger (1985, p. 124 f.).

last decade. In the following, we will review prominent applications of this methods in the field of supply chain management, real options analysis, and new product development.

2.2.2.2 Applications in Supply Chain Management Literature

Bayesian analysis has probably been the first updating method applied to the above discussed inventory and supply chain problems with uncertain demand patterns. Dvoretzky et al. (1952) were the first who studied Bayesian models to learn about future demand by combining prior distribution with additional information. Scarf (1959, 1960) derives an adaptive optimal order policy depending on the past history for the case of exponential demand distributions. Other contributions to this stream of research have been developed, for example, by Iglehart (1964) or Waldmann (1979) who are mainly concerned with deriving and characterizing optimal inventory replenishment policies. Noteworthy is the work of Azoury (1985) who models a periodic review inventory problem with several unknown parameters of the demand distribution as a Bayesian dynamic program with a multidimensional state variable.[11] The still prevailing problem by that time of computational intractability limited the attractiveness of Bayesian analysis. Non-Bayesian formulation of inventory problems as an approximation to the Bayesian dynamic programs turned out to be not equivalent as Azoury and Miller (1984) show. More recently, the interest in Bayesian analysis increased again. Lariviere and Porteus (1999) examine an empirical Bayesian inventory problem and derive optimal policies for both single and multiple market settings while Lovejoy (1990) studies exponentially smoothed forecast updates as well as Bayesian updates for myopic inventory policies.

Besides these Bayesian demand updates for the presented inventory problems, Bayesian analysis received special attention over the last decade in the Quick Response movement. Since the problem structure of these models is quite similar to ours of making preliminary decisions in NPD projects, we will have a closer look on these models. QR is an initiative of the apparel industry with the intention to reduce inventory costs in the supply chain by cutting manufacturing and distribution lead times through means such as better information exchanges between the participants, logistics improvements, and improved manufacturing methods.[12] The related decision problem corresponds to the above mentioned one of making decision under

[11] By considering distributions such as the gamma, uniform, Weibull, and normal, she extends the work of Scarf (1959) to other common classes of distributions where the known prior distribution is chosen from the corresponding natural conjugate family.

[12] For further details of this movement, the interested reader is referred to the excellent overviews of Hammond (1990) or Hunter (1990).

preliminary information: A buyer (e.g., a fashion retailer) places orders to a manufacturer over certain quantities before the actual demand is known. The retailer's trade-off of ordering too little, with the result of product stock-outs and low service levels (lost profit), or too much, with the result of increased holding costs and forced markdowns (additional costs), corresponds to the problem of the classical "newsboy" model[13] (cf. e.g., Nahmias 1997).

In the presence of long lead times and high demand uncertainties, as they are characteristic for the fashion industry for example, the (ex post) optimal order quantity is hardly ever met. To improve the decision making under such demand uncertainties, the classical newsboy model is extended for the QR environment by incorporating information updates of the initial demand estimates (Iyer and Bergen 1997). This allows the participants in the supply chain to delay the final quantity commitment until a later point in time when additional information becomes available. More precisely, the buyer can order some portion of the overall demand based on his initial estimates far ahead of the selling season. The costs of these items are relatively low as the production can be precisely planned and the long lead time allows to manufacture in low-wage countries. These prior estimates are then updated at a later point in time with data observed from related items, requests from trade fairs (e.g., fashion shows), or first orders received. Based on the adjusted demand estimates, a second order quantity can be placed for the remaining selling period if required. However, this quantity generally causes higher costs since the manufacturer has to resort to fast production modes, produce in plants close to the target market, or use a faster, but also more expensive conveyance (Kim 2003).

The developed models addressing the described decision problem provide insights into optimal order strategies (Fisher and Raman 1996; Eppen and Iyer 1997), e.g., the optimal order quantity at the different decision points, or show the benefits of QR for the different supply chain members (Iyer and Bergen 1997). Given our research objective, we are, however, solely interested in the applied updating mechanism. As indicated before, the update of the demand in these decision models is generally modeled in a Bayesian manner. Two major types of formulations can be found. The first group of authors assume that the initial and the total demand of a certain product is bivariate normal distributed (cf. e.g., Fisher and Raman 1996; Kim 2003; Gurnani and Tang 1999). This is one of the simplest distributional choices often made in Bayesian analysis since it allows to determine relative simple expressions for the moments (i.e., mean and variance) of the updated (posterior) demand distribution. The drawback is, however, that

[13] Also referred to as the newsvendor or newsperson model by overly politically correct persons. We take the latitude to ignore such nonsense and retain the original nomenclature.

such a distributional relationship has to be empirically validated. Without at least some indications of a bivariate normal relationship between the initial and total demand, the derived results have no practical relevance. Some authors like Kim (2003) or Gurnani and Tang (1999) ignore this prerequisite. They only take the benefits of the computationally convenient updating formulation without proving its applicability. Although the estimation and validation of demand densities and the corresponding parameters is a challenging task (Fisher and Raman 1996), it is the only way to justify the choice of this formulation.

For all other cases, where such a simplification is not applicable, one can still rely on commonly known distributions by applying the above mentioned concept of conjugate families where a prior distribution is chosen that is conjugate to the corresponding likelihood function. This updating formulation can be found, for example, in the QR models of Iyer and Bergen (1997) or Eppen and Iyer (1997). Although the determination of the posterior distribution is mathematically more complex, it is the only approach to develop an insightful model with practical relevance when the empirical validation of the chosen distribution is omitted or corresponding data is sparse. As the next section will show, the few R&D decision models of this type rely therefore on the concept of conjugate families.

2.2.3 Updating Mechanisms in R&D Models

The presented concepts of information updating have – albeit with significantly less effort – also been applied to decision problems in the field of R&D. In their influential work, McCardle (1985) and Lippman and McCardle (1987) develop a stopping model for management who faces the decision problem of adopting an innovative technology. Since the profitability of a new technology is quite uncertain at the moment of its announcement, management has to estimate its expected returns. However, prior to making the decision whether or not to adopt the technology, the firm has the possibility to sequentially gather additional information and to use it to update its initial profitability estimates. The update of the expected returns is modeled in a Bayesian manner assuming a conjugate relationship between the firm's prior distribution about the economic value of the technology and the distribution from which the information is generated.[14]

The model provides a clear policy for the information updating process. As soon as one of the two identified thresholds is crossed, the firm should stop the collection of additional information. In case that the upper limit is

[14]McCardle (1985) studies information structures which rely on the following conjugate families: Beta-Bernoulli, Gamma-Poisson, Gamma-exponential, and normal-normal, where the mean is unknown.

met, management should adopt the new technology, while the lower one indicates to reject it. Lippman and McCardle show that a higher precision of the prior distribution shortens the decision to adopt an innovation. In addition, better information (a sharper signal) only leads to the same effect if the precision of the signal is higher than the one of the prior distribution. Otherwise, it results in a delay of the decision.

These results are also studied in the presence of competition in a game-theoretic extension of this model provided by Mamer and McCardle (1987) who show that an increased expected level of substitutive competition reduces the probability that the firm will adopt the technology. Finally, Lippman and McCardle (1991) extend the sources of uncertainty in the model by adding to the uncertainty about the economic viability of a known technology the emergence of a new and unknown technology during the decision process. In a slightly different context, Krishnan and Bhattacharya (2002) focus on the role of design flexibility in the technology selection process and compare different design approaches (parallel path versus sufficient design).

Other models that address the management of preliminary information in NPD projects focus more on the exchange or the management of such information, e.g., Bhattacharya et al. (1998) who study the timing of product definition in highly dynamic environments where uncertainty is resolved through frequent, repeated interactions with customers. Since all these frameworks have in common that they do not focus on the update of information in a particular manner, but model preliminary information as a possible set of design parameters (Sobek et al. 1999; Krishnan et al. 1997) or a stream of engineering changes (Loch and Terwiesch 1998; Ha and Porteus 1995), they are not of interest to our research objective and hence, not further reviewed.

The reason for the few applications of information updating models to NPD problems lies – compared to the above discussed supply chain management models – in the complexity of the development projects and the underlying information structures. Loch and Terwiesch (2005) claim that the topology of the decision and outcome spaces underlying the currently existing decision models in the field operation management is not suited for NPD settings. Whereas in the supply chain management models, like the Quick Response models for example, the decision (how much to order) and the outcome (realized demand) correspond to a one-dimensional, ordered decision space, the information exchange in a NPD environment is more complex. In a product development project for example, where concurrent engineering is applied, multiple interdependent development activities are performed in parallel in order to shorten lead time (e.g. Krishnan et al. 1997; Loch and Terwiesch 1998; Terwiesch et al. 2002). Thus, information about several design specifications have to be exchanged simultaneously, each consisting of a set of multiple possible outcomes, i.e., the information structure and the decision space are multidimensional.

Loch and Terwiesch (2005) therefore use in their insightful decision model based on preliminary information the concept of information structures. In contrast to the one-dimensional structures of the currently existing Bayesian updating models, these information structures consist of set-based probabilities – formally represented by a sigma field – that are refined over time. In other words, the preliminary information is represented as a space of relevant outcomes where the aggregated events of incomplete information become known over time. The costs of the actions are assumed to increase over time. Modeling the decision problem as a two-stage stochastic dynamic program, the authors are able to derive optimal policies in dependence on the underlying cost structure as well as the available information gain. They show that waiting for more information and avoiding actions in an early period is the optimal policy if the cost increase is moderate. However, if building costs are so high that it is worth to delay actions while cancellation costs are not too high, the optimal managerial policy is iteration, i.e., take more targeted actions early and then adapt when new information becomes available. Finally hedging, i.e., starting with several actions simultaneously, is the optimal strategy if early actions are cheap compared to late ones.

With this decision model, Loch and Terwiesch provide one of the first quantitative frameworks for decision making based on preliminary information that applies to NPD projects. Although this model demonstrates the impact of cost and information characteristics on the optimal decision, it is less suited, as the authors claim themselves, to quantitatively evaluate managerial decisions. In addition, it does not allow to explicitly determine the value of additional information. But especially the latter aspect is of particular interest in NPD projects as it enables the assessment of the uncertainty reduction through an information update as well as its impact on the overall project value in financial terms. In the next section, we will therefore review financial methods that provide means for such a valuation.

2.3 Real Options Analysis

One key success factor of new development projects is, as the discussion in the previous section has shown, to understand the underlying uncertainty and respond to it accordingly. Although investments in such projects are generally irreversible, management often has the possibility to adjust its course of action during the development process as the uncertainty is gradually resolved with the arrival of new information. This flexibility to respond contingent upon additional information in such investment projects represents a value for the company that is neglected by the traditional investment valuation methods. Real options theory, by contrast, takes this operational flexibility in the valuation of such projects explicitly into account and is therefore well suited for our research objective.

In the following, we will briefly discuss the shortcomings of the traditional valuation approaches before giving an overview of the basic characteristics of real options and the corresponding valuation methods. Afterwards, we review key real options frameworks with applications to R&D projects and present first attempts of combining information updating with real options analysis. The focus will be on the concepts and contributions most relevant for our problem setting. For an in-depth survey of this growing area, see the comprehensive review of Lander and Pinches (1998) or the textbooks of Trigeorgis (1996) and Amram and Kulatilaka (1999).

2.3.1 Shortcomings of Traditional Valuation Methods

Most companies base their investment decisions on the results of traditional discounted cash flow analyses (Newton et al. 1996; Graham and Harvey 2001). These methods, like the net present value (NPV) or internal rate of return analysis for example, make implicit assumptions about the investment project under consideration. Since these measures require precise estimates about the generally uncertain future payoffs of the project in order to determine its value, they implicitly assume that the estimated revenues will actually occur. Moreover, they value the project solely on a go/no-go basis, i.e., the project can either be conducted now or never. Thus, they neglect the possibility to postpone the project for a certain period until additional information becomes available and (some) uncertainty is resolved. For these reasons, the discounted-cash-flow methods are not well suited for valuing NPD projects (cf. Kulatilaka and Marcus 1992; Haley and Goldberg 1995; Baecker et al. 2003).

Incorporating risk in the NPV analysis by adjusting the discount rate accordingly does not address the issue of imperfect cash-flow forecasts. Companies therefore frequently apply additional analysis methods like sensitivity analysis, traditional simulation, or scenario analysis. Sensitivity analysis allows to identify the key variables determining the cash flows and hence, their impact on the NPV. By analyzing the relative importance of a variable compared to the other ones, this analysis method indicates the riskiness of the different parameters and the potential impact of a misestimation on the project success. It studies, however, only the effect of one variable on the project value at a time while holding the other variables constant. Thus, it ignores interdependencies between the different variables (cf. e.g., Trigeorgis 1996, p. 52 f.).

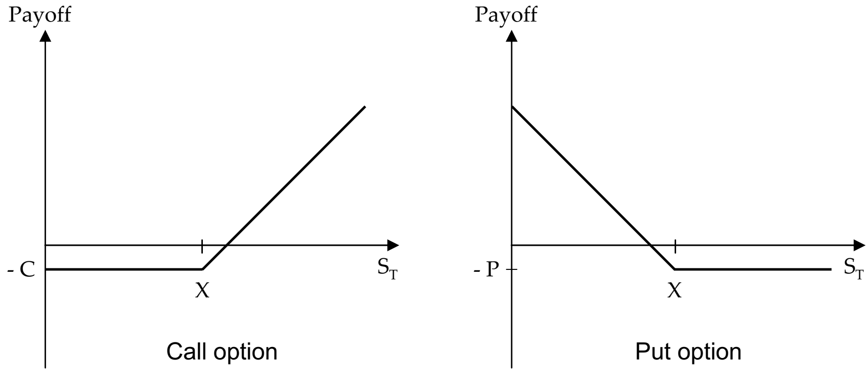
This deficiency can be addressed by traditional simulation techniques, like Monte Carlo simulation. Instead of varying the primary variables determining the NPV once at a time, simulation methods specify the different variables with probability distributions obtained from empirical studies or subjective estimates and describe their interdependencies as well as their impact on the project value through a mathematical model. By using large-scale random samples from the probability distributions of all critical variables, a probability distribution of the NPV for the assumed investment strategy is obtained. The characteristics of the decision problem under uncertainty and the interdependencies of the different input variables can thus be captured and analyzed. One has to be aware, however, that it is generally very difficult to describe all project-inherent interdependencies of the different variables exhaustively and to precisely estimate their probabilities a priori. In addition, one has to be careful not to double-count for risk if the NPV is already determined based on a risk adjusted discount rate (Myers 1976). Moreover, as a forward-looking technique, simulation analyzes an a priori specified investment strategy, thus ignoring the managerial flexibility to adjust the preconceived decisions to upcoming contingencies.

Finally, scenario analysis is another frequently applied method to capture the underlying uncertainty of an investment. It studies possible future events by considering possible alternative outcomes. Most commonly, three different cases are studied, e.g., the most likely one as well as a worst and a best case scenario. The consideration of extreme cases, which is generally only insufficiently addressed in traditional simulations techniques due to the low probabilities of extreme values, improves the simple NPV analysis. By allowing for a more complete consideration of outcomes and their implications, the obtained insights from a scenario analysis improve the basis for investment decisions.

Although each of the just presented approaches accounts in its particular way for the project inherent uncertainty, as it is particularly characteristic for new product development projects, neither one incorporates the managerial operating flexibility to respond to contingencies or additional information. In other words, they all ignore the value to adapt the initial strategy contingent on the possible states of nature (outcomes) in order to capitalize favorable future opportunities, e.g., to defer, expand, contract, or abandon the project. Thus, they systematically underestimate the true value of the investment. However, for the correct valuation of a project, these existing real options have to be taken into account. Due to their close analogy to options on financial assets, the corresponding valuation methods developed in this area can be applied to determine the actual value of the project. Before describing these methods in greater detail, a brief characterization of the different real options will be given.

2.3.2 Real Options

An option is the right, but not the obligation, to take a certain action in the future contingent on the realized state of nature. It is thus valuable in the presence of uncertainty. In finance, a call option gives the holder the right, with no obligation, to acquire the underlying asset (with a current value V) for an a priori specified price (the strike or exercise price X) on or before a certain date (maturity date T). Similarly, a put option gives the right to sell the underlying asset for the exercise price. If the option can be exercised only at maturity by paying the option price C (for a call) or P (for a put), this type of option is referred to as a European option, while an American option also allows for an execution before maturity.



Source: Adapted from Hull (2003).

Fig. 2.3. Payoff pattern of a European call and put option at maturity

The benefit of an option results from its asymmetric payoff function (see Fig. 2.3). The reason of this one-sided payoff structure is that one will only exercise the option if it yields for the at maturity realized state of nature a positive payoff for its holder, i.e., a call option will be exercised only if the price of the underlying asset on that date exceeds the exercise price. Hence, an option allows to utilize the upside potential while limiting the downside risk.[15] If the underlying asset of the option is not a financial security, but the gross project value of discounted expected cash-inflows from investments in

[15]Contrary to options, financial contracts (e.g., forwards) have a symmetric payoff structure as they involve a commitment to fulfill an obligation undertaken to buy or sell an asset in the future at the terms previously agreed upon, regardless of the development of the underlying asset (McDonald 2003, p. 21 ff.).

Table 2.1. Comparison between financial call option and real option

Real option on NPD project	Variable	Financial call option
Present value of expected cash flows	S_0	Underlying stock price
Investment costs	X	Exercise price
Expiration date of opportunity	T	Maturity
Project value uncertainty	σ	Volatility of underlying stock
Risk-free interest rate	r	Risk-free interest rate

Source: Adapted from Trigeorgis (1996, p. 125).

real assets, like manufacturing plants, oil field exploration, or machinery for example, these options are called *real options* (cf. Myers 1977, 1984; Kester 1984). They are in contrast to financial options not specified by a contract, but embedded in capital-investment opportunities and have therefore to be explicitly identified. Table 2.1 depicts the close analogies between a real option and a financial call option.

Among the many real options identified to date, the literature distinguishes the following basic types, classified primarily by the source of (managerial) flexibility (cf. e.g., Trigeorgis 1996; Copeland and Antikarov 2001):

- Option to defer: This option allows management to delay its commitment to an investment project, e.g., new manufacturing plant, until additional information becomes available which justifies the expenditures. It is therefore particularly valuable in settings where management has the possibility to reduce the uncertainty (e.g., market uncertainty) over time through learning (cf. e.g., McDonald and Siegel 1986; Ingersoll and Ross 1992).
- Option to expand: This option can be viewed as a call option on an existing project to acquire an additional part of the base-scale project or to extend it by a certain percentage. It will therefore only be exercised if the future market development turns out to be favorable. Since it allows the company to capitalize future growth opportunities, the option to expand is of particular strategic importance. Birge (2000) shows how the value of additional capacity can be expressed in terms of option value, which leads to an application in capacity-planning.
- Option to contract: In analogy to the option to expand, this option type allows management to reduce the scale of its production if the market conditions, e.g., demand, price, volume, etc., turn out to be less favorable than initially expected (cf. e.g., Pindyck 1988).
- Option to abandon: This option provides management with the possibility to terminate a project permanently in exchange for its salvage value

(cf. e.g., Myers and Majd 1990). The execution of this option may be beneficial if the current or future payoffs of a project do not even compensate for the fixed costs anymore. It thus provides a form of insurance against project failure. One should consider, however, not only all costs the termination may incur, but also take the loss of valuable expertise, organizational capabilities, or market access into account. The option to abandon is found, for example, in capital-intensive industries or new product development projects with high market uncertainty.

- Option to switch: The option to switch allows a company to change its mode of operation. This includes, for example, the option to temporarily shut down production and restart it later when the market conditions have improved (cf. e.g., McDonald and Siegel 1985). If the demand or the price of a certain product changes, the firm may also have the possibility to switch between alternative outputs (product flexibility). In the presence of such volatility, it may be valuable to invest in a more expensive, but also more flexible production mode that allows to adjust the output in accordance to the market development (Van Mieghem 1998). Similarly, management may be able to adjust the input to maintain the same output (process flexibility). This flexibility cannot only be achieved through an appropriate technology, as Kulatilaka (1993) shows considering the operation flexibility of a dual-fuel industrial steam boiler, but also through a flexible production or supply chain network.
- Option to improve: Introduced by Huchzermeier and Loch (2001), the option to improve represents the managerial flexibility in a new product development setting to take corrective actions during the development process in order to improve the performance of the product. The practical relevance of this option has been shown, for example, by Santiago and Bifano (2005) who value a high-technology development project in the presence of technical uncertainties.

In real-life investment projects, some of these just described real options may lead to interrelated opportunities which contain themselves other real options, i.e., compound options (cf. e.g., Geske 1979). Following Trigeorgis (1996, p. 132 f.), one can distinguish interactions between options on the same underlying project (interproject compoundness) and interactions embracing several underlying assets (intraproject compoundness). An example of the former compoundness is an investment in a R&D project which provides at its completion the opportunity for subsequent product generations or related applications. In this case, the subsequent projects are interdependent on the first one. In other words, the initial R&D project may lead to a whole chain of interrelated projects which in turn will offer future growth opportunities (Childs et al. 1998).

A multi-stage project, where an earlier investment is the prerequisite for the acquisition of the subsequent option to continue or extend the project, is an example for an intraproject interaction. Another example would be a project with several real options that are, if combined, simultaneously upward-enhancing and downward-protective. Brennan and Schwartz (1985) were the first who addressed this issue by studying the operation of a mine with the options to shut down and restart or to abandon it for its salvage value. A similar compound option in the context of a NPD project has been analyzed by Huchzermeier and Loch (2001) as well as Santiago and Vakili (2005). They analyze a project with an improvement option to increase the technical product performance by investing in additional resources – thus enhancing the upside potential of the project – and a coexisting abandonment option that simultaneously provides a protection against the downside risk.

Note that such interactions may affect the value of the real option. Trigeorgis (1993) has shown that the existence of subsequent options leading to further opportunities may increase the value of the effective underlying asset for earlier options. This leads in case of multiple interacting options on the same underlying to the fact that the separate option values do not necessarily add up, i.e., the combined value of the different options may differ from the sum of their separate values – they are so-called subadditive. Since this issue does not occur in our model, we will not further elaborate on this aspect, but refer the interested reader to the discussion in Trigeorgis (1993) or Kulatilaka (1995).

2.3.3 Valuation of Real Options

Due to their close analogy to financial ones, real options are valued by applying the concepts developed for pricing financial options. The seminal work of Black and Scholes (1973) and Merton (1973) marked the breakthrough in the valuation of financial options by providing a closed-form solution. They showed that – in an arbitrage-free world[16] – the price of an option equates the cost for setting up a continuously traded portfolio of the underlying security and a risk-free bond that exactly replicates the payoff of the option. The resulting partial differential equation can be solved in closed form, which is now known as the Black-Scholes option pricing model. The value of a European call option C can be determined as follows:

$$C = SN(d_1) - Xe^{-rT}N(d_2), \tag{2.1}$$

[16] The no arbitrage principle is also known as the "law of one price" which states that two investments with identical payoffs at all times and in all states must have the same value (cf. Brealey and Myers 1996, p. 961 f.).

where $d_1 = (\ln(S/X) + (r + \sigma^2/2)T)/\sigma\sqrt{T}$, $d_2 = d_1 - \sigma\sqrt{T}$, and $N(\cdot)$ is the cumulative standard normal distribution function.[17] The underlying assumption of the pricing model is that the stock price follows a stochastic Markov process that can be described by a geometric Brownian motion (or Wiener process).

A simplified valuation approach for options in discrete time was developed by Cox et al. (1979) where the stock-price movements follow a multiplicative binomial process. This model has proved to be very powerful in handling complex options and gained particular relevance for the valuation of real options in staged investments, like NPD projects that typically follow a stage-gate process. Especially if the resulting lattice tree is recombining, the underlying stochastic process can be well illustrated and the valuation of the real options in a backward recursive manner is intuitively traceable even for non-specialists.

The contingent claims analysis builds upon the basic risk neutral argument of Cox and Ross (1976). At the heart of this idea lies the above mentioned recognition that an option can be replicated from a continuously adjusted portfolio of traded securities. Since the value of the tracking portfolio and the option are independent of the investors' risk preferences, the valuation of the option can thus proceed in a risk-neutral manner, i.e., the expected future payoffs, weighted with risk-neutral probabilities, can be discounted at the risk-free interest rate. In other words, to value the managerial flexibility of an investment project, management neither has to estimate the probability of the future revenues nor the expected rate of return as long as a tracking portfolio can be created that incorporates the risk and return trade-off.[18] This makes the real options approach on the one hand a powerful tool, but limits on the other hand its practical applicability.

In many real-life settings, these underlying assumptions of real options valuation do often not apply (e.g., Lander and Pinches 1998; Brockhoff 2000; Witt 2003). Contrary to the valuation of financial options where the price of the underlying security is known from efficient financial markets, real options valuation lacks a corresponding market. The present value of an investment project (real asset) is generally not traded and thus, depends on subjective estimates. Although Trigeorgis (1993) as well as Mason and Merton (1985) argue that a dynamic portfolio of traded securities, which has the identical risk characteristics as the non-traded underlying real asset in complete markets, is sufficient for the valuation of real options (i.e., the existence of a continuously trading opportunity of the underlying asset itself is not required), it still requires a perfect correlation of the risk structure.

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[17]For the definition of the variables, see also Table 2.1.

[18]The price of the underlying asset and its volatility has of course to be determined.

However, investment projects in real assets, and NPD projects in particular, have often idiosyncratic risks that are uncorrelated with financial markets (Huchzermeier and Loch 2001). Thus, the by options theorists favored contingent claims analysis has limited applicability.

Decision scientists, on the other hand, rely on the alternative approaches of decision trees and stochastic dynamic programming models to determine the value of real options (cf. Bonini 1977; Dixit and Pindyck 1994, p. 93 ff.). These models capture the decision maker's beliefs about the outcome of the project by assessing subjective probabilities for the uncertainties while representing the preferences for project cash flows by a risk-adjusted discount rate. The latter aspect, however, raised major criticism by options theorists, e.g., Trigeorgis and Mason (1987) or Mason and Merton (1985), who claim that the problem of finding the correct discount rate remains unsolved in these models. Smith and Nau (1995) therefore propose a combined approach that results – when including market opportunities in the decision tree analysis and capturing time and risk preferences through a utility function – in the same project value and optimal strategy as contingent claims analysis. Unlike in the latter model, subjective beliefs and preferences play a critical role in this integrated valuation approach. For an application of this model to oil explorations projects see Smith and McCardle (1998).

Regardless of these two valuation philosophies with their particular advantages in specific settings on the one hand, but known shortcomings on the other hand, real options analysis in the broader sense is the appropriate method to determine the value of an investment project under uncertainty when management has the flexibility to respond to new information. It has therefore received increasing attention from academics as well as practitioners in the last decades (cf. e.g., Graham and Harvey 2001). Traditionally, many real options valuation models and practical applications can be found in the area of natural resource exploration projects, like oil drilling or mining projects, where the above mentioned difficulty regarding the replicating portfolio does not occur due to the existence of similar traded assets (e.g., Brennan and Schwartz 1985; Cortazar and Schwartz 1998; Cortazar et al. 2001; Kamrad and Ernst 2001).

Real options frameworks more directed towards operations management issues are less abundant. Kulatilaka (1988), for example, develops a stochastic dynamic programming model to value the flexibility in a manufacturing system stemming from the possibility to operate in different alternative modes. Kogut and Kulatilaka (1994) analyze the operating flexibility to shift production between two manufacturing plants located in different countries while Huchzermeier and Cohen (1996) focus on different manufacturing strategies exercised contingent upon exchange rate realizations in a global production network. Investments in flexible production capacity are valued by He and Pindyck (2002) who model this capacity choice problem as a singular stochastic control problem. For further references on real options frameworks focusing on product and operations management, see the comprehensive reviews of Lander and Pinches (1998) and Miller and Park (2002).

2.3.4 Models and Applications for R&D Projects

Besides the above mentioned application areas, real options valuation obtained special attention in the field of R&D since it is an ideal approach to value the managerial flexibility of responding to the high level of technology and market uncertainty inherent in these projects. In addition, the sequential development process of the projects fosters the application of the real options framework since it can be regarded as a series of investments, each containing one or more real options, like extending a project or switching to a different technology, for example. In the following, we will present some insightful frameworks that are of interest to our research objective.

Baldwin and Clark (1998, 2002) analyze the option value of modularity in product design. As such a design increases the flexibility to respond to (late) market requirement changes and makes the complexity in development projects manageable, it has substantial value. They show that the option value of a modular design approximately corresponds to the net option value inherent in each module less the cost of creating the modular architecture. Childs et al. (1998) develop a real options framework to study the optimal investment policy for product development projects that can either be developed in sequence or in parallel. Their analysis reveals that the optimal development strategy depends on the volatility, the correlation between the project's present values, as well as the development cost and time. Loch and Bode-Greuel (2001) focus on the complex sequential decisions in drug development projects and examine the inherent compound real options with a decision tree valuation framework.

Lint and Pennings (2001) use a real options approach to develop a framework that addresses market and technology uncertainty in a development project. They treat NPD as a sequential process in which management has the following options at the different stages: Extend the efforts to large scale R&D after the evaluation of the initial product idea screening, conduct R&D without the obligation of launching the project, invest in further validation of the product's market potential, and finally, launch the product into the market. With this framework, they compare R&D project portfolios containing these options that are exposed to different degrees of uncertainty. The already mentioned framework of Huchzermeier and Loch (2001) as well as the extension of Santiago and Vakili (2005) allow to evaluate flexibility in a single R&D project in the presence of compound real options. In contrast to

Lint and Pennings, they examine multiple sources of uncertainty (e.g., budget, schedule, technical performance, market requirements) and extensively address the distinction between these sources of operational variability and financial uncertainty.[19] As it allows to value not only the common option of abandoning the project, but also explicitly considers the possibility of taking corrective action in order to improve the technical performance and hence, the project payoff, this model is very realistic and insightful for valuing NPD projects. This makes it well suited for our decision problem. We will therefore provide a more thorough description of the model in Section 3.1.

Although these frameworks explicitly address the managerial flexibility to respond accordingly when uncertainty is resolved, they do not incorporate learning as an explicit element. The acquisition of new information is rather viewed as a passive consequence of the project progression. However, some approaches exist that address this issue. Childs and Triantis (1999), for example, study dynamic investment policies for a R&D program where management has the possibility to reduce uncertainty through investments in the development process. In particular, they model two R&D projects with a three-dimensional lattice tree and demonstrate how collateral learning between the projects as well as a dynamically altering funding policy (e.g., accelerating, shelving, or abandoning projects) affect the optimal investment policy.

Bellalah (2001) analyzes investment decisions under uncertainty and incomplete information with a continuous-time model. By explicitly accounting for information costs regarding the project cash flows, he is able to discuss the impact of these costs on the project value. Martzoukos and Trigeorgis (2001) explore the reduction of uncertainty in investment opportunities. By using a real options framework with incomplete information and costly learning actions that induce path-dependency, they show that optimal timing of information acquisition is essential as it reduces the cost of potential mistakes and hence, increases the value of investment opportunities. As additional information is generally costly, management has hereby to trade-off between the quality and the cost of learning.

The explicit incorporation of learning in these frameworks is predominantly modeled by considering corresponding costs for information. Thus, information acquisition is rather studied from a cost than from a decision making perspective. However, some attempts exist that combine statistical decision theory with real options analysis in order to incorporate information updates in a Bayesian manner. These models will be presented next.

[19] A practical application of this model to a high-tech NPD project is presented by Santiago and Bifano (2005).

2.3.5 Attempts of Combining Bayesian Analysis and Real Options

Herath and Park (2001) are one of the first who explore the idea of combining Bayesian analysis with real options. They develop a simple valuation framework based on the concept of the expected value of perfect information. With this approach, they study investment decisions where management has the option to defer a project until more information becomes available. The model allows for sequential revaluations of the project using sampling information in a Bayesian manner to reduce future uncertainty at each decision point.

Miller and Park (2005) build on this decision theory framework and develop a real options model that incorporates information acquisition through a Bayesian update. They model a contingent multi-stage investment scenario where management uses the information obtained after the first investment phase of the project to update the initial estimates of the expected future cash flows. Contingent on the adjusted estimates, the updated option value for the remaining project is determined and the decision about the next investment phase is made, i.e., whether to continue the project or not (other managerial options are not considered). Depending on the number of considered stages, this updating and decision procedure is repeated. Although the updating method applies the before mentioned normal conjugate relationship, it is one-dimensional and only allows for updates of the mean. The derived insights are therefore limited. The only key finding is a threshold which defines when the firm's prior decision is reversed based on the observed sample result.

A primarily practical application of a framework that combines Bayesian analysis with real options is presented by Armstrong et al. (2005). They study the option value of acquiring additional information for an oilfield production enhancement project. In this case, management has to value the investment in a workover of an oil well in order to maintain hydrocarbon production at a satisfactory economic level. Besides the choice between simply continuing the production and conducting a workover based on the currently existing information, management has also the possibility to increase the efficiency of the workover by conducting a study about the reservoir. The results obtained from this costly study can be used to update the initial information about the benefit of a workover. To determine the value of this additional information, the authors incorporate Bayesian analysis into a real options framework. More precisely, they assume that the two sources of uncertainty, the underlying oil prices and the characteristics of the reservoir, are bivariate normal distributed. Using Monte Carlo simulation to compute the option prices based on the assumed distributions, they are able to identify a threshold value for the oil price when the acquisition of the additional information is valuable.

These two recently published models are, to the best of our knowledge, the first attempts which combine Bayesian analysis with real options frameworks. Although both models are quite simple in their structure and provide only limited managerial implications, they clearly show that the combination of these two methods is a well-suited approach to value information updating.

2.4 Summary

The review of the relevant strands of literature in this chapter clearly indicates the need for more quantitative models to improve decision making in NPD projects that are inherently exposed to a high degree of uncertainty (see Fig. 2.4 for a summary). Although numerous empirical studies identify the timely generation of information (particularly in the early phases of the development process) as a key success factor and stress the need for regular updates, hardly any formal models exist. Most of the derived managerial insights are obtained either from normative or empirical studies. However, only quantitative models allow to determine the project specific optimal response to additional information by explicitly incorporating the underlying parameters, like development costs, time, expected payoffs, etc. In addition, they allow to study the impact of these parameters on the optimal solution and to determine the value of an information update during the development process.

The problem of making decisions under preliminary information is not limited to NPD. We have seen that other areas of operations management, like supply chain management for example, face similar challenges. The developed decision models in these fields apply various information updating methods to optimize operations by reducing the inherent uncertainty as time progresses. While time series methods or Markov models require sufficient historical data to extrapolate the future development or to model the underlying process of the unknown parameter(s), Bayesian updating allows to combine (subjective) prior estimates with additional information in a straightforward manner and hence, is best suited to model the uncertainty reduction in NPD projects.

Some first attempts exist which explicitly model information acquisition via Bayesian updating in a real options framework. By combining these two methods, one is able to determine the value of information acquisition. However, these rather simple models have neither a primary focus on NPD projects nor do they address the NPD specific characteristics like multidimensional information structures. Thus, an information updating model for NPD projects must address these characteristics as well as the typical sources of uncertainty. An insightful real options framework that allows to

Area	Insights for Thesis	Differences to Thesis	Key References
New Product Development	• Information generation and updating is a key success factor • Lack of decision/valuation models for early stages of NPD projects • Design flexibility in highly uncertain environments has high impact on project success	• Research studies are largely descriptive • Primarily qualitative managerial insights provided • Dependency of optimal decision on underlying parameters not addressed	• Mahajan (1992) • Thomke (1997) • Krishnan and Loch (2005)
Real Options Theory	• Well suited framework to value managerial flexibility in NPD • Integration of improvement option as a managerial action to increase expected performance • Only few attempts for integration of information updates exist	• Only one source of uncertainty explicitly modeled • No explicit determination of information updating value • Uncertainty reduction regarded as a passive process	• Huchzermeier and Loch (2001) • Santiago and Vakili (2005) • Miller and Park (2005)
Decision models with information updates	• General set-up to model decision making under uncertainty • Topology of outcome space has to address NPD characteristics • Integration of information updates with methods of Bayesian analysis	• Applied Bayesian updating models have only one-dimensional state space • Only mean updates considered • Insufficient focus on NPD problem structure	• Berger (1985) • Iyer and Bergen (1997) • Loch and Terwiesch (2005)

Thesis

Fig. 2.4. Summary of literature

value managerial flexibility in NPD project is the model of Huchzermeier and Loch (2001) and the extension by Santiago and Vakili (2005). It considers not only the in NPD widely applied option to abandon a project in case of an unfavorable technical or financial development, but also takes the possibility of corrective actions to improve the technical performance into account. This makes the framework well suited for NPD applications as well as for a base case of an information updating decision model. It will therefore be presented in greater detail in the next chapter.

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