Determining Optimal Investment Strategies –
On the Economic Evaluation and Analysis of Investments

Kumulative Dissertation

der Wirtschaftswissenschaftlichen Fakultät

der Universität Augsburg

zur Erlangung des Grades eines

Doktors der Wirtschaftswissenschaften

(Dr. rer. pol.)

vorgelegt

von

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Augsburg, Juni 2017

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Datum der mündlichen Prüfung:	31.07.2017

“Hoffnung ist nicht die Überzeugung, dass etwas gut ausgeht,

sondern die Gewissheit, dass etwas Sinn hat,

egal wie es ausgeht.”

Václav Havel (05.10.1936 – 18.12.2011)

Tschechischer Schriftsteller, Menschenrechtler und Politiker

Table of Contents

Please note: Tables and figures are consecutively numbered per chapter, and within Chapters II, III, and IV per section (each representing one research paper). References are provided at the end of each section and each research paper, respectively.

Index of Research Papers

Research Paper 1:
Häckel B, Pfosser S, Stirnweiß D, Voit Ch (2018) Determining Optimal Strategies for Investments in an Emerging IT Innovation.
In: *Twenty-Sixth European Conference on Information Systems (ECIS2018), Portsmouth, UK.* **VHB-JOURQUAL 3: Category B**

Research Paper 2:
Häckel B, Lindermeir A, Moser F, Pfosser S (2017) Mindful Engagement in Emerging IT Innovations - A Dynamic Optimization Model Considering Organizational Learning in IT Innovation Investment Evaluation.
In: *ACM SIGMIS – The Data Base for Advances in Information Systems, 48(1).* **VHB-JOURQUAL 3: Category B**
https://doi.org/10.1145/3051473.3051477

Research Paper 3:
Häckel B, Lindermeir A, Moser F, Pfosser S (2016) Evaluating Different IT Innovation Investment Strategies from an *Ex Ante* and *Ex Post* Evaluation Perspective.
In: *International Journal of Innovation and Technology Management, 13(4).* **VHB-JOURQUAL 3: Category C**
https://doi.org/10.1142/S0219877016500152

Research Paper 4:
Pfosser S (2017) Bewertung und Planung von IT-Investitionen unter Berücksichtigung finanzieller Beschränkungen.
In: *Proceedings der 13. Internationalen Tagung Wirtschaftsinformatik (WI2017), St. Gallen, Schweiz.* **VHB-JOURQUAL 3: Category C**

Research Paper 5:
Häckel B, Pfosser S, Tränkler T (2017) Explaining the Energy Efficiency Gap – Expected Utility Theory versus Cumulative Prospect Theory.
In: *Energy Policy, 111 (2017).* **VHB-JOURQUAL 3: Category B**
https://doi.org/10.1016/j.enpol.2017.09.026

I Introduction

To ensure an economically sustainable long-term development of a company and to keep up with competition, a value-based evaluation of investments by means of appropriate methods is an ongoing issue of upmost importance for companies (e.g., Clark and Guy, 1998; Copeland et al., 2005; Nadler and Tushman, 1999). Thereby, especially investments in innovative technologies, aiming at strategic long-term goals, do heavily impact a company's economic situation, as they provide extensive chances but simultaneously bear substantial risks (e.g., Aral et al., 2007; Broy et al., 2012; Chui et al., 2010; Dess and Picken, 2000; Gartner, 2015; Lu and Ramamurthy, 2010; Swanson and Ramiller, 2004). On the one hand, such investments are supposed to enable and maintain substantial long-term success and high returns due to new business opportunities, or considerable savings due to increased cost efficiency (e.g., Barua et al., 2001; Porter et al., 1985). On the other hand, such investments require substantial financial resources (regularly for a longer planning horizon), and bear the risk that the desired long-term success cannot be realized as their further development is rather unsecure (e.g., Fenn and Raskino, 2008; Wang, 2010). In this context, different investment situations exhibit individual specifics that may change over time and influence the risk and return profile of an investment (Ross and Beath, 2002; Swanson and Ramiller, 2004). For example, the market potential of an innovative technology that may decrease when the technology loses its innovative character over time, or a company's individual ability to successfully implement a new technology that may increase due to experiences with similar investments. Consequently, an insufficient consideration of such influencing fac tors (e.g., due to an imprudent bandwagon behavior (Abrahamson, 1991; Wang, 2010)) leads to suboptimal or even wrong investment decisions, in a way that potential economic benefits often cannot be realized. Thus, to enable the determination of optimal investment strategies, i.e., an optimal allocation of scarce financial resources, tailored evaluation approaches are needed, that adequately cover individual influencing factors and their effects on the risk and return profiles of the investments.

Due to their vast economic impact, the evaluation of investments has been discussed in theory and practice for decades. By now, many different approaches and methods (e.g., Internal Rate of Return, Net Present Value, Real Option Valuation) based on different financial or economic theories (e.g., Utility Theory, Investment Theory, Portfolio Theory, or Option Pricing Theory) have been developed. Moreover, existing approaches are partially enriched by aspects of various disciplines (e.g., Psychology, Mathematics, or Information Engineering) (Copeland et al., 2005; Perridon et al., 2016). Hence, there are manifold approaches available, forming the basis for an economic evaluation of investments. However, to consider specific influencing factors and framework conditions of individual investment situations, available standard approaches have to be individually adjusted to quantitatively depict those influences on the risk and return profiles of desired investments (e.g., a rather innovative startup company with low financial funds that invests in an innovative IT vs. a not very innovative large corporation with sufficient financial funds that invests in the very same IT innovation). By means of such an assessment of the individual investment situation (including possible changes of relevant influencing factors), a reasonable support to determine optimal investment strategies can be provided. Therefore, a fundamental three step approach can be utilized (cf. Fig. 1).

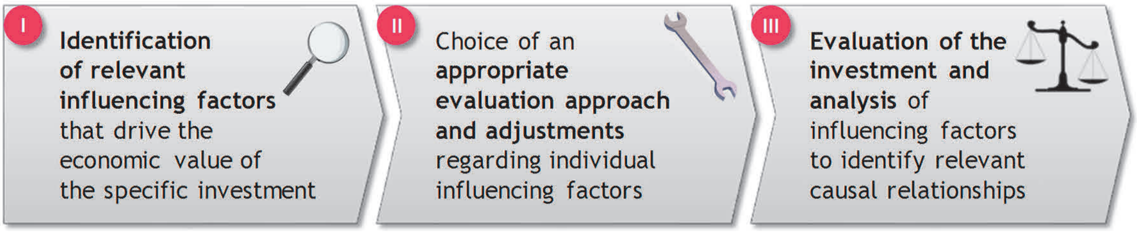

Figure 1. Fundamental steps for an economic evaluation of an investment

First, relevant factors and peculiarities of the specific investment situation have to be identified and their influence on the value of investment has to be estimated. To ensure a comprehensive collection of all (as far as possible) relevant influencing factors, not only the investment object itself has to be examined. Instead, also the market environment (e.g., potential market size, necessary marketing costs), and relevant company specifics (e.g., currently and future available investment budgets, existing knowledge regarding the investment) have to be taken into account. Additionally, dependencies between the different influencing factors have to be depicted to enable the identification of relevant direct and indirect causal relationships.

Second, existing evaluation methods and approaches (e.g., Net Present Value, Real Options Approach) have to be examined to identify the method that adequately covers the fundamental investment situation in line with the company's management principles (e.g., risk adjusted Net Present Value approach for a long-term investment of a company aiming at a value-based management). Building up on the chosen standard method, necessary adjustments (e.g., regarding the effects of considered influencing factors on future cash flows) have to be performed to obtain a tailored evaluation approach that depicts the specific influencing factors in a sensible manner.

Third, by means of the tailored evaluation approach, the evaluation itself can be performed, i.e., the economic value of the investment depending on the respective risk and return profile can be determined. However, investments regularly can be carried out with different specifications and internal and external factors may vary over time. Thus, an analysis should be performed to reveal the impact of changes in the considered influencing factors (e.g., by means of sensitivity analysis, or simulation) and thus, to identify and quantify relevant causal relationships. Based on the result of the evaluation and associated in-depth analysis, optimal investment strategies can determined.

Dealing with the outlined challenges, in this doctoral thesis three selected investment situations are addressed, which are, among many others, particularly important for companies (Chapters II, III, and IV):

(i) Evaluation of Investments in IT Innovations
(ii) Evaluation of Investments in IT Considering Financial Constraints
(iii) Evaluation of Investments in Energy Efficiency Measures

Investment situation (i) "Evaluation of Investments in IT Innovations"

Due to the ever increasing speed and multitude of technological developments like smart manufacturing, the internet of things, big data, virtual reality, cyber-physical (production) systems, or machine learning investments in IT innovations are a decisive challenge for companies of all sectors (Broy et al., 2012; Chui et al., 2010; Gartner, 2015; Wortmann et al., 2015). Thus, although almost all sectors and companies are already depending on IT, its importance for a sustainable business success is ever increasing, as innovative IT often is indispensable for creating new digital business models (Andal-Ancion et al., 2003; Aral et al., 2007; Barua et al., 2001; Porter et al., 1985; Ramirez et al., 2010). Consequently, companies are forced to continuously invest in IT innovations to keep up with rapid technological development, changing customer needs, and thus, to remain competitive (Atzori et al., 2010; A.T. Kearney, 2012; Clark and Guy, 1998; Dess and Picken, 2000; Porter et al., 1985; Zhu et al., 2003). One main challenge is the optimal timing of investments in emerging IT innovations, as their risk and return profiles are heavily depending on the development stage of the respective IT innovation. In this context, emerging IT innovations can be defined as new technologies which are not (yet) widely adopted but exhibit substantial economic potential (Häckel et al., 2017). According to the concept of "hype cycles" by Gartner Inc. (e.g., Gartner, 2015), the uncertain development of an emerging IT innovation is characterized by different stages of maturity. At the beginning of their development, emerging IT innovations are often accompanied by rumors and hypes (Abrahamson and Fairchild, 1999) until they become mature IT innovations, characterized by a broader diffusion and adoption. In the best case, they possibly become an institutionalized (i.e., widely adopted) technology in the long run. Thus, for example, early investments in emerging IT innovations promise substantial returns (due to first mover advantages) in case the technology will be successfully adopted by the market. However, such investments are also associated with high risk due to their highly uncertain development. In contrast, investments in more mature innovations are regularly associated with lower possible returns as first mover advantages (e.g., market leadership) cannot be realized anymore. At the same time, such investments bear lower risks as their market adoption can be predicted better based on their development so far. Moreover, the risk and return profiles of innovation investments are influenced by company-specific factors (e.g., organizational knowledge towards a certain technology) and the market environment (e.g., market potential of a new technology). Thus, companies are faced with rather different possible investment situations that are influenced by various specific factors. Besides timing aspects, determining optimal long-term strategies regarding the allocation of innovation budgets to IT innovations of different maturity is a major challenge. Thereby, chances and risks of investments in different kinds of IT innovations have to be considered to obtain a balanced risk and return profile. Additionally, to determine a sensible long-term investment strategy, it has to be considered that individual factors like a company's innovativeness (i.e., its ability to successfully engage in emerging IT innovations) develop over time and therefore have a changing influence on the risk and return profile of the investments. However, regarding investments in IT innovations, companies often decide on a gut-feeling, or chose rather fixed strategies for IT innovation investments (i.e., investment of a fixed share of the IT innovation budget) (Abrahamson, 1991; Wang, 2010), neglecting effects of varying influencing factors like the company's innovativeness due to organizational learning (Nagji and Tuff, 2012; Ross and Beath, 2002). This might lead to adverse investment decisions. Therefore, the overall goal for Chapter II is to provide adequately tailored evaluation approaches that enable the determination of optimal strategies for investments in IT innovations as well as analysis of important causal relationships.

Investment situation (ii) "Evaluation of Investments in IT Considering Financial Constraints"

IT investments often are projects that last over several periods and therefore require investment payments in several points in time for a successful completion. However, future financing of these investment payments is associated with uncertainty. For example, due to external shocks, unplanned internal reallocations or saving programs, leading to decreased investment budgets (Dedrick et al., 2003). Such a sudden significant reduction (or even elimination) of future investment payments due to financial constraints impedes the realization of the initially planned value contribution of the investment (Boyle and Guthrie, 2003; Campello et al., 2011; Cleary, 1999). Thus, the financing of future investment payments should be ensured to successfully complete the IT investment and obtain its planned value contribution. Additionally, due to their intangible nature, IT investments often cannot be used as collateral, what restricts the possibility for debt financing (Brynjolfsson et al., 2002; Brynjolfsson and Yang, 1997; Krcmar, 2010). However, financial constraints (i.e., low or risky financing possibilities) that limit or endanger financing possibilities of necessary investment payments are often neglected when evaluating and planning IT investments. Thus, an integration of finance and IT investment management that enables the consideration of financial constraints and their impact on the respective IT investment can help to ensure the desired value creation (Santhanam and Kyparisis, 1996). In this context, Chapter III aims at providing a tailored IT investment evaluation approach that enables the determination of an optimal investment strategy for IT investment projects considering financial constraints.

Investment situation (iii) "Evaluation of Investments in Energy Efficiency Measures"

To mitigate negative economic and ecological effects of climate change and the consumption of non-renewable resources, the increase of energy efficiency (EE) is a promising step (among others) (European Commission, 2016; Granade et al., 2009). Thereby, the positive ecological effects of EE measures are often associated with economic advantages, as the reduction of energy consumption leads to cost reductions. However, studies show that many investments in EE measures are not carried out, although they would be beneficial from an ecological and economic point of view. This so-called Energy Efficiency Gap (Brown et al., 1998; Rosenfeld et al., 1993) can be described as the "difference between the actual level of investment in EE and the higher level that would be cost-beneficial from the consumer's (i.e., the individual's or firm's) point of view" (Brown, 2001). This might be justified in evaluation biases, e.g., investors probably overestimate possible negative or underestimate possible positive effects of those investments which can significantly distort the perceived value of an investment. EE investments are therefore not carried out, since investors evaluate them "irrationally" due to behavioral biases (Barberis, 2013; Greene, 2011). Thereby, not only investments by institutional investors or companies have to be considered, but also investment decisions of private households. Different investments of private households, for example, in new light bulbs, the exchange of old electric appliances (e.g., refrigerator), or a thermal insulation of a house bear substantial energy saving potentials on an aggregated level (European Commission, 2017).

However, individuals are more likely to avoid complex evaluations and often decide just based on a gut feeling or perceived value. Additionally, they are prone to typical "evaluation errors", e.g., neglect of alternative investment opportunities or consideration of only a part of the investment's lifetime leading to an underestimation of possible future energy savings (Greene, 2011). To derive helpful recommendations to overcome the Energy Efficiency Gap, it is necessary to understand and quantitatively evaluate investments in EE measures based on different theoretical frameworks to cover both, "rational" and "irrational" behavior. Chapter III therefore aims at quantitatively explaining the Energy Efficiency Gap by applying different valuation frameworks (Expected Utility Theory and Cumulative Prospect Theory) by analyzing causal relationships to derive recommendations regarding actually optimal investment levels.

In summary, the adequate depiction of specific investment situations to enable an economically well-founded evaluation as basis for the determination of optimal investment strategies is an ongoing issue for research and practice. Therefore, this doctoral thesis particularly contributes to the (i) evaluation of investments in IT innovations, (ii) the evaluation of investments in IT considering financial constraints, and (iii) the evaluation of investments in EE measures. The following Section I.1 illustrates the objectives and structure of the doctoral thesis. In the subsequent Section I.2, the corresponding research papers are embedded in the research context and the fundamental research questions are highlighted.

I.1 Objectives and Structure of this Doctoral Thesis

The main objective of this doctoral thesis is to contribute to the field of economic investment evaluation by developing tailored investment evaluation approaches that enable the determination of optimal investment strategies. Therefore, the doctoral thesis focuses on investments in IT innovations, investments in IT considering financial constraints, and investments in EE measures. The following table gives an overview of the pursued objectives and the structure of the doctoral thesis.

I Introduction	
Objective I.1:	Outlining the objectives and the structure of the doctoral thesis
Objective I.2:	Embedding the included research papers into the context of the doctoral thesis and formulating the fundamental research questions
II Evaluation of IT Innovation Investments Considering Different Risk and Return Profiles (Research Papers 1, 2, and 3)	
Objective II.1:	Providing an economical evaluation approach to determine the optimal strategy regarding the timing of investments in an emerging IT innovation
Objective II.2:	Identifying and evaluating crucial influencing factors and causal relationships regarding strategies for investments in an emerging IT innovation
Objective II.3:	Providing an economical evaluation approach to determine optimal dynamic long-term strategies for investments in IT innovations of different maturity considering organizational learning
Objective II.4:	Identifying and evaluating crucial influencing factors and causal relationships that impact dynamic long-term IT innovation investment strategies
Objective II.5:	Evaluating ex ante determined optimal dynamic long-term strategies for investments in IT innovations of different maturity from an ex post perspective and comparing them to other IT innovation investment strategies
Objective II.6:	Evaluating the economic impact of a company's innovativeness on investments in IT innovations of different maturity from an ex ante and an ex post perspective

III Evaluation of Investments in IT Considering Financial Constraints (Research Paper 4)	
Objective III.1:	Providing a quantitative evaluation approach to consider financial constraints within the evaluation and planning of IT investments
Objective III.2:	Identifying and evaluating the influence of varying financial constraints on the economic value of IT investments
IV Evaluation of Energy Efficiency Investments Based on Different Theoretical Frameworks (Research Paper 5)	
Objective IV.1:	Providing a quantitative approach to evaluate investments in EE measures based on Expected Utility Theory and Cumulative Prospect Theory
Objective IV.2:	Identifying and analyzing relevant influencing factors which can explain the so-called Energy Efficiency Gap
V Results and Future Research	
Objective V.1:	Presenting the key findings of the doctoral thesis
Objective V.2:	Identifying and highlighting areas for future research

Table 1: Objectives and structure of the doctoral thesis

I.2 Research Context and Research Questions

In the following section, the research papers included in this doctoral thesis are embedded in the research context with respect to the above stated objectives and the respective research questions are motivated.

I.2.1 Chapter II: Evaluation of IT Innovation Investments Considering Different Risk and Return Profiles

Research Paper 1: *"Determining Optimal Strategies for Investments in an Emerging IT Innovation."*

Due to technical developments such as the internet of things or smart factories, investments in innovative IT are becoming a factor of major influence for a growing number of companies. Companies regularly have to decide when and to what extent they want to invest in a chosen IT innovation. According to the concept of "hype cycles" by Gartner Inc. (e.g., Gartner, 2015), the risk and return profile of possible investments in an IT innovation considerably changes during their development from an emerging to a possibly institutionalized IT innovation. Investments at an early stage are expected to enable high returns in case of market adoption due to possible market or technology leadership, but simultaneously bear high risks, as the future development and long-term success of the IT innovation is quite uncertain (Fenn et al., 2008; Ravichandran et al., 2011; Rogers, 2003; Wang, 2010). In contrast, investments at a later point in time of the IT innovation's development only promise lower returns as market or technology leadership is regularly not achievable anymore but simultaneously bear lower risks, as the IT innovation already gained a certain degree of market adaption (Fenn et al., 2008; Wang, 2010). Besides this dynamic development, also company-specific factors (e.g., a company's ability to successfully implement IT innovations) influence the risk and return profiles of possible investments. However, in practice, such investment decisions often are not based on a well-founded evaluation (Abrahamson, 1991; Swanson and Ramiller, 2004; Wang, 2010) and adequate theoretical approaches are not available so far. Thus, research paper 1 aims to provide a quantitative evaluation approach that enables the determination of optimal strategies for investments in an emerging IT innovation, considering relevant influencing factors. Therefore, the following research questions will be answered:

- How can a company determine an optimal strategy for investments in an emerging IT innovation in terms of expected NPV?

- How do different company- and IT innovation-specific factors influence the optimal strategy and the expected NPV of investments in an emerging IT innovation?

Research Paper 2: *"Mindful Engagement in Emerging IT Innovations - A Dynamic Optimization Model Considering Organizational Learning in IT Innovation Investment Evaluation."*

Whereas research paper 1 focuses on the optimal strategy for investments in an emerging IT innovation, research paper 2 addresses the question of how to optimally allocate periodical innovation budgets to IT innovations of different maturity (Abrahamson and Fairchild, 1999; McAfee et al., 2008; Rogers, 2003; Swanson, 1994). As argued, the maturity of IT innovations heavily influences the risk and return profiles of associated investments. Thus, investments in emerging IT innovations exhibit different chances and risks than investments in mature IT innovations. To deal with these differences and to obtain a balanced IT innovation portfolio, companies have to determine optimal long-term investment strategies (Fenn et al., 2008). Besides specifics of the IT innovation (e.g., its probability of success), especially the company's innovativeness has a major influence on the risk and return profiles of investments in IT innovations. To determine sensible long-term strategies, in particular the change of the innovativeness over time due to organizational learning - i.e., an increasing innovativeness through continuous engagement in IT innovations - has to be considered. Consequently, the investment strategy has to be a dynamic one that is adjusted to the effects of organizational learning over time. Nevertheless, the determination of such dynamic long-term investment strategies often is not economically well-founded but taken based only on a gut feeling (Abrahamson, 1991; Swanson et al., 2004; Wang, 2010). Due to the lack of adequate theoretical evaluation approaches, research paper 2 aims to provide an approach to enable the determination of dynamic investment strategies to optimally allocate IT innovation budgets to different IT innovation investments. Thus, it deals with the following research questions:

- What is a company's optimal IT innovation budget allocation to emerging IT innovations as well as more mature IT innovations?
- How does organizational learning affect a company's optimal IT innovation budget allocation to emerging IT innovations, and how does the investment strategy change over time?
- How do selected company-specific and IT innovation-specific characteristics (e.g., an IT innovation's probability of success or the market's average engagement) influence the optimal innovation strategy?

***Research Paper 3**: "Evaluating Different IT Innovation Investment Strategies from an Ex Ante and Ex Post Evaluation Perspective."*

Ex ante determined optimal IT innovation strategies are of upmost relevance to enable a mindful and managed engagement in IT innovations. However, due to unforeseen changes, ex ante optimal investment strategies can turn out to be suboptimal from an ex post perspective. In this vein, literature provides numerous approaches which examine the business value of IT from an ex post perspective (Kohli and Grover, 2008). However, approaches that analyze how ex ante determined investment strategies for IT innovations perform from an ex post perspective are missing so far. Thus, research paper 3 substantially expands literature based on the preliminary work of research paper 2 by means of performing an *ex post* evaluation of *ex ante* determined optimal IT innovation investment strategies based on a mathematical approach. Similar to research paper 2 a dynamic long-term IT innovation investment strategy, i.e., an allocation of periodical budgets to IT innovations of different maturity considering organizational learning, is determined firstly (Nagji and Tuff, 2012; Swanson and Ramiller, 2004; Ross and Beath, 2002). Building on this *ex ante* optimal dynamic IT innovation investment strategy, secondly, different possible future scenarios are defined. Thirdly, from an *ex post* evaluation perspective, the performance of the *ex ante* optimal strategy within the defined scenarios is analyzed. Thereby, different baseline scenarios, e.g., regarding the company's innovativeness, are considered. By doing so, it is possible to examine whether the *ex ante* optimal strategy is also optimal from an ex post evaluation perspective. Additionally, the extent of the economic advantage or disadvantage of the *ex ante* determined optimal strategy compared to other possible strategies can be analyzed from an *ex post* evaluation perspective and regarding different baseline scenarios. Thus, it is possible to give an indication whether the *ex ante* determined optimal dynamic IT innovation investment strategy is systematically advantageous, even within unplanned scenarios, compared to other strategies. To enable this, research paper 3 focusses on the comparison of IT innovation investment strategies for different scenarios from an *ex ante* and an *ex post* evaluation perspective by answering the following research questions:

- From an *ex ante* perspective: Regarding the expected NPVs, to what extent do the optimal IT innovation investment strategies of companies with different abilities to innovate differ from each other?
- From an *ex ante* perspective: How substantial is the expected economic advantage of a theoretically optimal dynamic IT innovation investment strategy compared to a fixed

IT innovation investment strategy and how is this economic advantage influenced by a company's ability to innovate?

- From an *ex post* perspective: How does a company's ability to innovate influence the volatility of an optimal IT innovation investment strategy's economic success across different realized scenarios?
- From an *ex post* perspective: How do different scenarios and a company's ability to innovate affect the advantage of an ex ante determined optimal dynamic IT innovation investment strategy compared to a fixed IT innovation investment strategy?

I.2.2 Chapter III: Evaluation of Investments in IT Considering Financial Constraints

Research Paper 4: *"Bewertung und Planung von IT-Investitionen unter Berücksichtigung finanzieller Beschränkungen."*

IT investment projects regularly last more than one period until they are completely implemented. Thus, they require investment payments not only within the current but also in future periods. Within the planning of such IT investment projects, the financing of necessary future investment payments often is assumed to be ensured, or is neglected. However, the financing of future investment payments is associated with uncertainty, as there can be far-reaching negative changes in the financial situation of a company. Consequently, companies may be forced to large cutbacks of budgets on short notice which can lead to significant reductions, or even a complete withdraw of planned investment payments (Dedrick et al., 2003; Pettey and Stevens, 2011; Standish Group, 2010). Such financial constraints can heavily hamper the desired value creation of the IT investment project. Thus, companies should consider financial constraints at an early stage of the investment planning process to derive effective measures to protect the IT investment project's value creation. As the evaluation of IT investment projects supports the planning of their implementation (including necessary investment payments), financial constraints and possible counter measures should be considered within the economic evaluation of such projects to enable a sensible planning. In this context, an appropriate measure, based on finance literature (e.g., Bates et al., 2009; Ferreira and Vilela, 2004), is to build a strategic liquidity reserve that serves to hedge future necessary payments. By means of a transfer of the fundamental idea from finance to IT management, an improved management of IT investment projects could be enabled. Therefore, a combined approach based on finance and information management that enables the optimization of the expected value contribution of an IT investment project considering financial constraints is needed. Thus, research paper 4 provides such an approach and associated analysis to answer the following research questions:

- How can financial constraints be considered within an approach to evaluate and plan IT investment projects?
- How do financial constraints influence the optimal investment payments and the value contribution of an IT investment project?

I.2.3 Chapter III: Evaluation of Energy Efficiency Investments Based on Different Theoretical Frameworks

Research Paper 5: *"Explaining the Energy Efficiency Gap – Expected Utility Theory versus Cumulative Prospect Theory."*

Climate change and preserving non-renewable resources are global key challenges for policy, economy, and society (European Commission, 2012). To support the struggle against climate change and to mitigate its negative ecologic and economic effects, investments in EE measures are a promising measure as they enable extensive energy savings (European Commission, 2016; Granade et al., 2009). Besides ecological advantages, such measures often are also sensible form an economical point of view, as they act like an insurance against an increase of future energy prices. Therefore, EE investments should be pervasive measure for companies and individuals. However, research and practice show that there is significant evidence for the so-called Energy Efficiency Gap, i.e., a significant underinvestment in EE measures (Brown, 2001; Linares and Labandeira, 2010). Thus, despite their undisputed advantages, there is a lack of investments in both, ecologically and economically useful EE measures. In this context, according to classical Decision Theory, the Energy Efficiency Gap indicates "irrational" behavior as "rational" decision maker would carry out more EE investments. Helping to close the Energy Efficiency Gap, in a first step it is necessary to understand and analyze relevant factors, which might be causal for such an irrational behavior. Thereby, behavioral biases regarding the risk and return perception of individuals may be key factors which lead to a distorted evaluation of investments in EE measures (Barberis, 2013; Greene, 2011). For example, due to loss aversion, investors may overestimate possible losses in case the desired savings cannot be realized. Based on the analysis of possible influencing factors, recommendations for policy makers, helping to overcome the Energy Efficiency Gap, can be drawn. In this context, research paper 5 aims at an economic evaluation of investments in EE measures based on Expected Utility Theory and Cumulative Prospect Theory to identify relevant influencing factors of the Energy Efficiency Gap by answering the following research questions:

- Can the Energy Efficiency Gap be explained by a comparison of EE investment evaluations based on the Expected Utility Theory and the Cumulative Prospect Theory?
- Which elements of the Cumulative Prospect Theory are the main drivers of the Energy Efficiency Gap?
- What policy implications to overcome the Energy Efficiency Gap can be drawn based on the analysis?

I.2.4 Chapter V: Results and Future Research

After this introduction, which aims at outlining the objectives and the structure of the doctoral thesis as well as at motivating the research context and formulating the research questions, the research papers are presented in Chapters II, III and IV. Subsequently, Chapter V presents the key findings and highlights areas for future research in the fields of novel investment evaluation approaches regarding IT innovations, investments in IT considering financial constraints, and EE measures.

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II Evaluation of IT Innovation Investments Considering Different Risk and Return Profiles

The main challenge regarding investments in IT innovations is to determine a strategy that promises the most profitable allocation of available financial resources considering risk and return aspects. This is rather complex as several factors (e.g., the IT innovation's maturity, or the company's innovativeness) heavily influence the economic value of such investments. Additionally, investments in one selected emerging IT innovation constitute different investment situation than the allocation of recurring budgets to IT innovations of different maturity (e.g., regarding relevance and influence of the timing of the investments). In practice, associated investment decisions regularly are just based on a gut feeling and companies fail to achieve the investment's maximum possible value contribution. Therefore, economically well-founded evaluation approaches considering relevant influencing factors can support the determination of optimal investment strategies. Chapter II contributes to this field by providing appropriate evaluation approaches.

The first research paper *"Determining Optimal Strategies for Investments in an Emerging IT Innovation."* (Section II.1) develops and analyzes an evaluation approach to determine optimal strategies for investments in an emerging IT innovation. Thereby, the most common, but at the same time most different investment strategies – *First Mover*, and *Late Mover* – are considered. Furthermore, to derive hypothesis regarding important causal relationships, and recommendations for a practical application, several possible investment situations are modeled and analyzed.

The second research paper *"Mindful Engagement in Emerging IT Innovations – A Dynamic Optimization Model Considering Organizational Learning in IT Innovation Investment Evaluation."* (Section II.2) develops and analyzes an evaluation approach to determine the ex ante optimal dynamic investment strategies regarding the periodical allocation of IT innovation budgets to IT innovations of different maturity. Thereby, especially changes of a company's innovativeness due to organizational learning and its influence on the investment strategy is modeled and analyzed in order to derive insights regarding relevant causal relationships.

The third research paper *"Evaluating Different IT Innovation Investment Strategies from an Ex Ante and Ex Post Evaluation Perspective."* (Section II.3) also analyzes strategies regarding investments of periodical IT innovation budgets in IT innovations of different maturities based on a quantitative evaluation approach. However, the focus of the paper is not on the ex ante determination of the optimal investment strategy but on ex post analysis of ex ante determined investment strategies. Thus, it is possible to analyze whether an ex ante determined investment strategy is also beneficial from an ex post perspective and whether a dynamic IT innovation strategy outperforms fixed investment strategies.

II.1 Research Paper 1: "Determining Optimal Strategies for Investments in an Emerging IT Innovation."

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In:	Twenty-Sixth European Conference on Information Systems (ECIS2018), Portsmouth, UK

Abstract:

To generate competitive advantages through investments in emerging IT innovations, an economically well-founded investment strategy is of decisive importance, since timing and extent of investment amounts considerably determine the associated risk and return profile. Due to the uncertainty about emerging IT innovations, an early market entry time is associated with high risk, but offer high returns. A later market entry may carry lower risk but only offers lower returns. To take advantage of both investment strategies while reducing their disadvantages, a mix of both investment strategies can be advantageous. Companies often choose strict early or later investment strategies since an adequate assessment of possible combination opportunities and risks is not carried out in advance and company- and innovation-specific factors are neglected. Thus, we develop a quantitative optimization model

enabling the determination of an optimal investment strategy and budget allocation to the two different investment strategies in the sense of maximizing the investment´s overall NPV supplementing previous studies by considering company- and IT innovation-specific factors. We show that strict investment strategies are often disadvantageous, that the amount of the investment budget influences the innovation´s expected NPV and that the company's innovativeness has a strong influence on the innovation budget allocation.

II.1.1 Introduction

The role of information technology (IT) in the field of innovation has often been discussed (Melville et al., 2004) and studied for decades (Johannessen, 1994; Bengtsson and Ågerfalk, 2011). As we are in an era of new technological advances and high competition, the question of how a company can keep pace with competition through organizational innovation and maintain sustainable long-term success (Sedera et al., 2016) is still of central interest. Given trends such as smart manufacturing, internet of things (IoT), mobile computing, social media and the proliferating digitalization, most emerging innovations are inseparably intertwined with information technology. For a majority of companies, investments in emerging IT innovations have become an indispensable challenge since such investments require substantial financial funds and at the same time, pose considerable risks (Lu and Ramamurthy, 2010; Swanson and Ramiller, 2004). However, such investments require substantial financial funds and at the same time, pose considerable risks given that many emerging IT innovations are likely to be failing because of missing customer acceptance due to missing fulfillment of customer expectations and needs (Lu and Ramamurthy, 2010; Swanson and Ramiller, 2004). Thus, investments in emerging IT innovations have to be mindfully managed through economically well-founded evaluation approaches, as ignoring such investments can limit the inherent benefits of applications that the underlying technologies can offer (Nwankpa et al., 2013).

Therefore, in a first step it is helpful to consider the concept of "hype cycles" by Gartner Inc. (e.g., Panetta, 2017), according to which the uncertain development of an emerging IT innovation is characterized by different stages of maturity. At the beginning of an "*emerging*" innovation´s development the innovation is often accompanied by rumors and hypes (Abrahamson, 2009) and investments are associated with high risks (Zhou et al., 2005; Wind and Mahajan, 1997). Over time, the IT innovation becomes more and more sophisticated turning into a "*mature*" innovation. In this way, the innovation gains more and more acceptance by customers which leads to a broader diffusion and adoption making investments less risky (Dos Santos, Brian L and Peffers, 1995). As soon as the innovation has been widely accepted by customers, it has been established, i.e., "institutionalized". However, the Gartner Hype Cycle does not provide any economic guidance with regard to the question of when to invest into a certain IT innovation. In particular, it provides neither information on opportunities and risks nor information on the economic potential of IT innovations. To be able to make economically well-founded investment decisions, adequate valuation approaches have to be developed that carefully consider the chances and risks of IT innovations with different maturity. This is of essential importance, as the chance and risk profile of such investments considerably changes over the life cycle of the respective IT innovation.

Because of their novelty and immaturity, emerging IT innovations offer companies that invest as *first mover* (FM) the chance to achieve a high level of awareness among customers (Mittal and Swami, 2004). Because of their high level of awareness, FM can quickly generate high market shares (Robinson, 1988; Kerin et al., 1992) and build up much knowledge due to their early market entry. This can lead to a technological leadership and enables them to “impose significant knowledge barriers that early adopters have to overcome” (Schmalensee, 1980; Ravichandran and Liu, 2011), in order to compete successfully against established FM. In contrast, later investments as *late mover* (LM) in mature IT innovations are often associated with lower risks since the development and adoption status of the underlying technology are already visible (Meade and Islam, 2006; Dos Santos, Brian L and Peffers, 1995). Mistakes that FM made in the development of emerging IT innovations are well known by LM and can thus be avoided (Hippel, 1982). Furthermore, LM rely on already partially developed technologies and continues to develop it further, which induces lower costs than completely redeveloping an innovation Dos Santos, Brian L and Peffers, 1995). Additionally, they benefit from an already existing pool of customers, whose expectations and needs are already known, thereby reducing the risk that the innovation will fail (Dos Santos, Brian L and Peffers, 1995).

Given the complex trade-off and owing to management uncertainty, e.g., due to the lack of relevant data, companies often tend to apply a strict black-or-white investment strategy (i.e., a pure FM or LM). However, a “mixed” investment strategy (i.e., one part of an investment budget is allocated to a FM investment and the other part to a LM investment) entails the possibility of combining the advantages of an FM and an LM strategy and avoiding their disadvantages at the same time to reach a superior risk and return profile and outperform strict FM or LM strategies. Therefore, an economically well-founded ex-ante evaluation, regarding an optimal allocation of the budget to emerging and mature innovations is needed at an early stage since FM advantages cannot be realized later on once an IT innovation emerges. Beside the chances and risks of the different investment strategies (emerging vs. mature) it is also important to identify relevant specifics of the underlying IT innovation (e.g., estimated market impact in different scenarios) and the company (e.g., company’s ability to innovate successfully) that can significantly influence the investment decision. This allows us to cover various essential framework conditions to derive fundamental hypotheses regarding scenarios in which investing as FM in an emerging innovation is beneficial towards investing as LM in a “mature” innovation.

To the best of our knowledge, there is no quantitative optimization model, combining relevant company- and innovation-specific parameters, success- and failing-probabilities and considering a “mixed” investment strategy to calculate the optimal allocation of an investment budget for emerging and mature IT innovations to maximize the NPV´s of the underlying investments. Conducting sensitivity and scenario analyses, we aim to uncover relations between the identified parameters thus enabling a deeper understanding of how different parameters influence the optimal allocation of an investment budget. Thereby, we contribute to one of the fundamental research questions in IT innovation literature of *when* and *to what extent* a company should invest in an emerging IT innovation with deriving the following two research questions (RQ´s):

> **RQ1:** *How can a company determine an optimal strategy for investments in an emerging IT innovation in terms of expected NPV?*
>
> **RQ2:** *How do different company- and IT innovation-specific factors influence an optimal strategy and the expected NPV of investments in an emerging IT innovation?*

The remainder of this paper is organized as follows. Following a discussion of the relevant literature in section 2, section 3 develops our quantitative optimization model. Section 4 presents the model’s solutions, exemplary applications, and sensitivity analyses. Section 5 summarizes the findings and limitations and provides suggestions for future research.

II.1.2 Theoretical Background and Related Literature

In this section, we draw on IT innovation literature to define IT innovation and its possible development inspired by the concept of hype cycles. We also discuss the literature on investments in emerging IT innovations and parameters influencing decisions regarding optimal investment strategies. Thus, this section lays the theoretical foundation for our quantitative optimization model.

II.1.2.1 IT Innovations

Swanson (1994) defines IT innovations as "innovations in the organizational application of digital computer and communications technologies (now commonly known as information technology)." Garcia and Calantone (2002) define (IT-)innovation as the generation and/or acceptance of ideas, processes, products, and services that are new to the company or the company´s customers. It is a generalized view of innovation taking into account innovation occurring in all kind of organizations. It goes beyond the definitions that stated innovation as "new to the world" (Garcia and Calantone, 2002). We refer to a definition of Crossan and Apaydin (2010) that stated innovation as the "production or adoption, assimilation, and exploitation of a value-added novelty in economic […] spheres; renewal and enlargement of products, services, […]; development of new methods of production; and establishment of new management systems". This definition includes internally initiated innovations, as well as adopted innovations.

Basically, we can distinguish two types of innovations. Depending on their "newness", innovations can be incremental *(mature)* or breakthrough *(emerging)*. Mature innovations refer to minor changes in technology or simple product improvements. In contrast, emerging innovations are novel, unique, or state-of-the-art technological advances in a product category (Wind and Mahajan, 1997; Zhou et al., 2005). Emerging innovations are highly risky to pursue (Zhou et al., 2005). On the one hand an emerging innovation may be technologically risky because developing state-of-the-art technology is extremely expensive and requires substantial investments (Wind and Mahajan, 1997). However, even if an innovation may be technologically straightforward, it can be extremely risky on the market side because the consumers acceptance is highly uncertain (Christensen and Bower, 1996).

An innovation's development over time can be explained by Gartner Inc.'s concept of hype cycles (for the current version, see Panetta, 2017), which illustrates the possible developments of an emerging IT innovation through several stages. The development begins with a *technology trigger* with excess publicity, leading to over-enthusiasm and investments often influenced by bandwagon behavior. Thus, within their lifecycle of adoption (Rogers, 2003), IT innovations are often "hyped," that is, accompanied by waves of discourse or rumors about the innovation itself and its adoption and diffusion (Abrahamson and Fairchild, 1999). This hype typically reaches a peak of *inflated expectations* before it fades away in a *trough of* *disillusionment*. For our upcoming model, we summarize these first three stages within a first of two development periods by mapping them through the first of two consecutive discrete points in time and refer to investments within these first three stages as FM-investments.

However, in this early stage, substantial adoption is missing, and evaluation with reliable estimations of future evolution is almost impossible owing to the hype that might fade in the absence of long-term productivity. Today, IT innovations such as Connected Homes, Blockchain and Machine Learning can be classified as *emerging IT innovations* (Panetta, 2017). In contrast, *mature IT innovations* have already been adopted by a substantial part of the market (Rogers, 2003), demonstrating that they were not just a hype and exhibiting stable development (Fenn and Raskino, 2008). Thus, their future evolution can be roughly estimated. For instance, virtual or augmented reality can be classified as mature IT innovations (Panetta, 2017). Only a few technologies will reach the status *"mature"* at the end of the first period of development and are worthy of further investment and hard work to understand the technology's applicability, risks, and benefits, leading to a *slope of enlightenment* followed by a *plateau of productivity* (Fenn and Raskino, 2008; Wang, 2010). For our upcoming model, we summarize these two stages within the second of two development periods by mapping two consecutive discrete points in time and refer to investments within these two stages as LM-investments. Finally, *institutionalized IT innovations* are innovations that have been established in the market and acquired mass adoption beyond the plateau of productivity. Also, they have crossed the chasm from being an IT innovation to an established technology. As the Gartner Hype Cycle only provides information about the current development status of an innovation and is not suitable for planning investments due to a lack of information about opportunities, risks and economic potential, we develop a mathematical model that calculates an optimal allocation of an investment budget to emerging and mature innovations on the basis of investment-related information specific to the innovation, market and company, which we will motivate and explain in more detail in the upcoming section.

II.1.2.2 Investments in IT Innovations

The advent and massive proliferation of digitalization and its corresponding IT applications (e.g., mobile computing, cloud computing, social media, etc.), fueled by the consumerization of IT (Harris et al., 2012) provided companies with flexible and cost-effective opportunities to innovate (Vodanovich et al., 2010). Technology advancements over the past few years have assisted companies in innovation through a variety of helpful improvements and decision support systems (e.g. improved decision-making capabilities, increased customer connectedness, increased number of communication channels, enhanced communication facilities) (Huber, 1990; Brynjolfsson, 2011; Kumar et al., 2010; Bharadwaj, 2000; Nambisan, 2016). Therefore, investments in emerging IT innovations are beneficial to (Melville *et al*., 2004) and essential for companies (Clark and Guy, 1998; Nadler and Tushman, 1999).

However, investments in new IT innovations remain a risky challenge, e.g. due to uncertainty about future market penetration and the literature does not provide any information on how an investment budget should be allocated optimally to IT innovations of different stages of maturity. Therefore investments are often driven by market pressure and bandwagon behavior (Häckel et al., 2017), thus lacking an economically well-founded decision calculus. In order to avoid investments on a gut feeling when choosing an optimal investment strategy, but considering the peculiarities of IT innovations (e.g., probability of institutionalization, expected economic impact of technology, or market innovativeness) and the current development status according to the Gartner Hype Cycle, our optimization model includes parameters that reflect these peculiarities and the current development status. To ensure that the investment decision is also optimal in an economic sense, we select the maximum net present value of the underlying investments as an optimality criterion. By applying such a model, complex interdependencies between key factors can be mapped and considered in investment decisions. Furthermore, we also consider company-specific factors (e.g., company size, investment budget, structure, and agility) influence the risk and return profile of investments in emerging IT innovations. Thus, a company’s ability to understand, successfully adopt, and implement IT innovations are key factors as the introduction of new technologies imposes “substantial burden on the adopter regarding the knowledge needed to understand and use them effectively” (Ke and Wei, 2006). This ability to be a successful innovative company can be designated as a company’s *“innovator profile”*. Companies that fit this profile are expected to innovate more easily, effectively, and economically (Fichman, 2004b). Furthermore, systematic innovators have more experience in selecting and implementing IT innovations in an early phase and can better evaluate new applications (Swanson and Ramiller, 2004). Thus, a company’s success with investments in emerging IT innovations depends on not only on the underlying technology’s customer acceptance but also the company’s innovator profile (Fichman, 2004b). We incorporate the key capabilities mentioned by Ke and

Wei (2006) and denoted as innovator profile in our model in the form of a further parameter. That makes it possible to consider effects caused by a high respectively low innovator profile mentioned by Fichman (2004b) on the optimal allocation of an investment budget.

When choosing a suitable investment strategy, the timing of the investment plays also a major role. Thus, depending on the investment timing, innovation investments undergo different risk and return profiles and some prior studies focused on the evaluation of emerging IT innovations and the effects on IT innovation investment strategies. For instance, Dos Santos and Pfeffers (1995) demonstrated advantages of engagements in emerging IT innovations given the possibility of adding over-proportional value. Lu and Ramamurthy (2010) examined investment strategies in stable and dynamic settings and demonstrated that proactive IT innovation leaders who regularly engage in emerging IT innovations outperform reactive IT innovators in overall performance and cost efficiency.

Wang (2010) found that companies improved their performance and gained a better reputation owing to over-proportional returns resulting from long-term competitive advantages based on investments in emerging IT innovations. Using game theory, Hoppe (2000) showed that under certain conditions, even second-mover strategies could be advantageous because of spillover effects. However, these studies neither incorporate the risk of non-institutionalization, nor provide advice about the extent and timing of investments, nor explain how an investment budget should be allocated between emerging and mature IT innovations. In a first approach, Häckel *et al*. (2013) considered the risk of a failing emerging IT innovation and examined the error resulting from fixed investment strategies regarding the allocation of periodical IT innovation investment budgets; however, they did not analyze the concrete decision situation of a company that aims to optimize the budget allocation over time for an emerging IT innovation.

However, there is a lack of quantitative approaches that investigate optimal “mixed” strategies e.g. in terms of timing and budget allocation that entail the possibility of a beneficial combination of an FM and LM investment to reach a superior risk and return profile and may outperform strict FM or LM strategies.

Furthermore, other insights into whether an investment strategy for an innovation will be successful are often based on statistical evaluations of historical data of similar companies with similar investment behavior (FM vs. LM). Therefore, by using those studies recommendations for a certain investment strategy can be given under known conditions. However, since these results cannot be generalized and transferred to other scenarios, investment strategy decisions cannot be made on economically well-founded basis in previously never occurred environmental scenarios.

In sum, the current status in relevant research primarily reveals gaps by either neglecting relevant (company-specific) parameters, focusing on strict investment strategies or building up on historical data which cannot be generalized and applied on different companies or scenarios.

Thus, drawing on related literature, the present study develops a quantitative optimization model to determine an optimal investment strategy considering relevant parameters in sense of calculating an optimal allocation of an investment budget to emerging and mature IT innovations. Using findings from prior research, we analyze the impact of different company- and IT innovation-specific influencing factors using exemplary applications and sensitivity analyses. This can provide new insights and propositions for future research and empirical testing.

II.1.3 The Model

We consider a company that has decided to invest in an emerging IT innovation. Before making an investment decision, the company must determine the optimal strategy regarding timing and allocation of an available amount of "innovation budget" to maximize the innovation´s expected NPV. Our model covers strategies for a *„first mover"* investment in an emerging IT innovation, a *"late mover"* investment in a mature IT innovation, and the possibility of a mixed investment strategy, which might enable a superior combination of the LM and FM risk and return profiles. To cover the possibility of the IT innovation developing over time, the model's time frame comprises three points in time. An FM investment is possible at the first point in time wherein the IT innovation emerges, and an LM investment is possible at the second point in time. At the third point in time, the development of the IT innovation is complete, and its final destiny becomes obvious.

Assumption 1 – Initial Situation:

At $t = 0$, a company chooses a strategic budget $B \in \mathbb{R}^+$ for investments in an emerging IT innovation. At the same time, the company must determine the share $x \in [0; 1]$ of B

invested at $t = 0$ *(FM investment). The other share of budget* $(1 - x)$ *is saved for a possible investment at* $t = 1$ *(LM investment).*

Assumption 2 – Uncertainty about IT Innovation's Development

a) Possible Scenarios for Development: *The development of an IT innovation is uncertain and broken down into two periods: from* $t = 0$ *to* $t = 1$ *(period one) and from* $t = 1$ *to* $t = 2$ *(period two). Within both periods, a positive (upside: "u") and negative (downside: "d") scenario is possible, whereas a positive scenario within period one implies a development into a mature IT Innovation and a positive scenario within the period two implies a development into an institutionalized IT Innovation. However, a negative development in both periods implies a failing IT Innovation. After a negative development within the first period, a second period of development is not considered because the IT innovation has failed. At* $t = 2$*, the IT innovation's development is completed and one of the scenarios* $s \in \{uu, ud, d\}$ *is realized.*

The breakdown of an IT innovation's development in two periods is inspired by Gartner's hype cycle (Fenn and Raskino, 2008) and enables an appropriate depiction of an IT innovation's development within our quantitative model. It covers the entire process from when an IT innovation emerges to the outcome (Wang, 2010). Thus, relevant changes in the characteristics of an IT innovation, which should be accounted for in an economically well-founded evaluation, can be adequately considered (e.g., decreasing uncertainty about the possible long-term success of an IT innovation).

b) Probabilities of the Development Periods: *The uncertainty about the future IT innovation development is described by the probability* $p_t \in [0; 1]$ *with* $t \in \{0; 1\}$ *for positive (u) development and* $(1 - p_t)$ *for negative (d) development within the first and second period. The probability for a positive development is considerably lower in the first than in the second period* $(p_0 < p_1)$.

The probability of positive development in the first period (p_0) indicates the probability of an emerging IT innovation is becoming a mature one. This probability is rather low since many emerging innovations fail after the first period of development when the hype vanishes (Gourville, 2006). When the IT innovation has survived the first period, it demonstrates marketability thus far and the first indications of market acceptance can be observed (e.g., sales of beta-versions or results of customer surveys). Meanwhile, other competitive

IT innovations have already failed within the first period and thus, only those IT innovations that passed the first "endurance test" reach the second period of development and thus the risk of investing in a failing technology is getting lower. Therefore, the probability of a positive development in the second period (p_1) is considerably higher than the probability (p_0). The probabilities for the upside and first and second downside scenarios $s \in \{uu, ud, d\}$ can be calculated by the probabilities $p_t \in [0; 1]$ designated for the two periods of development (Fig. 1).

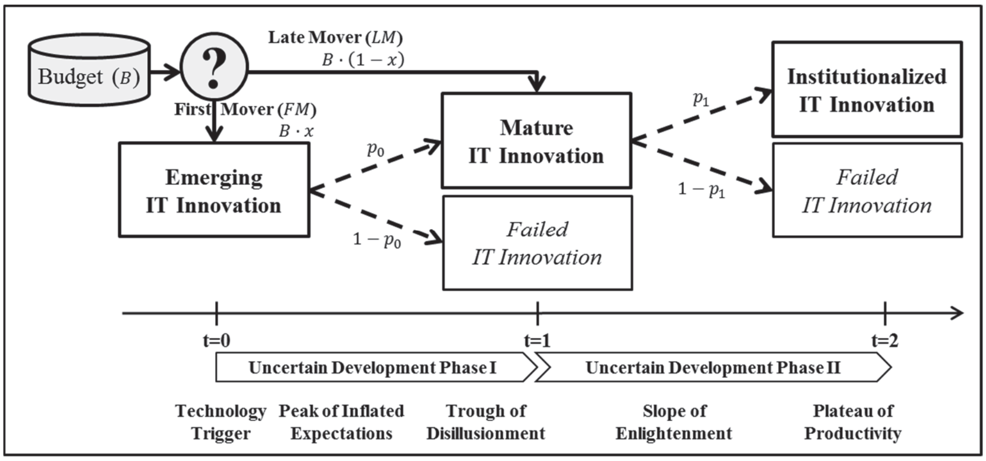

Fig. 2 Overview of the model's decision situation

Assumption 3 – Achievable Future Cash Flows

a) Parameters of Cash Flow Functions: *The resulting cash flow $CF_j(ep_j^s, B, x)$ depends on the invested share x of budget B, the budget B itself and the investment's economic potential $ep_j^s \in \mathbb{R}$, $s \in \{uu, ud, d\}$, $j \in \{FM, LM\}$. For the upside scenario ($s = uu$), an FM investment is associated with higher economic potential than an LM investment ($ep_{FM}^{uu} > ep_{LM}^{uu}$). On the other hand, for downside scenarios $s \in \{ud, d\}$, the FM investment's economic potential (ep_{FM}^{ud} and ep_{FM}^{d}) is equal or less than an LM investment (ep_{LM}^{ud}). In addition, the economic potentials for the upside scenario are considerably higher than those for the downside scenarios:*

$$ep_{FM}^{uu} > ep_{LM}^{uu} \gg ep_{LM}^{ud} \geq ep_{FM}^{ud} = ep_{FM}^{d}. \qquad 1.$$

Economic potentials as IT innovation-specific factors depict the extent of possible long-term returns. They cover the IT innovation's expected market impact according to factors such as consumers' acceptance, market competition, or the probability of easy integration into the company's existing IT infrastructure (Fichman, 2004c; Haner, 2002; Moser, 2011). The factors influence the extent of resulting cash flows and can be estimated through market analyses or internal and external educated guesses by technical experts or those with comprehensive market experience and an appropriate understanding of the emerging innovations´ potential.

If the emerging IT innovation becomes institutionalized in the long run, the investments result in positive cash flows. The highest possible cash flow results from an FM investment since these investments tend to generate higher cash flows for a company owing to FM advantages (Lu and Ramamurthy, 2010; Wang, 2010). Therefore, for the upside scenario, the economic potential of an FM investment (ep_{FM}^{uu}) is higher than that for an LM investment (ep_{LM}^{uu}).

For the downside scenarios, there are three possible cases depicted by our assumption (eq. 1): low positive, zero, or negative cash flows when the IT innovation fails. Thus, the factors covering economic potentials within the cash flow functions are also positive, zero, or negative. First, low positive cash flows are possible if there are no inevitable cash outflows in the future but low cash inflows, for example, if the IT innovation can be partly used or exploited otherwise. Since an FM investment is associated with a deeper engagement in the IT innovation, what impedes a quick switch to another use of the IT innovation, an LM investment enables slightly higher positive cash flows. Second, if no future cash inflows or outflows are possible when the IT innovation fails, this leads to zero cash flows. Thus, the economic potentials are the same: $ep_{LM}^{ud} = ep_{FM}^{ud} = ep_{FM}^{d} = 0$. Third, negative cash flows are possible if future inevitable cash outflows occur, for example, owing to reputational damages or performed organizational changes. Thereby, the cash flows of a FM investment are lower (i.e., more negative) than those for an LM investment due to a longer and deeper engagement. In addition to the described possible cash flows, necessary investment expenditures are also considered in our NPV approach (assumption 5). Thus, even for low positive cash flows, the NPV of the investment can become negative.

b) Course of Cash Flow Functions: *The cash flow $CF_j(ep_j^s, B, x)$ follows a strictly monotonically increasing and concave function.*

A monotonically increasing, concave function is suitable to depict an increasing but diminishing marginal utility according to production theory (Stiglitz, 1993), which is appropriate for cash flows resulting from investments in an emerging IT innovation for several reasons. First, the monotonically increasing course depicts that a higher investment leads to deeper engagement, making deeper understanding and broader implementation possible (Fichman, 2004b; Kimberly, 1981; Melville et al., 2004). Second, a first engagement in an IT innovation enables entering a market or becoming reasonably familiar with a technology (Lu and Ramamurthy, 2010; Stratopoulos and Lim, 2010), and therefore, creates a higher marginal cash flow than an increase in an already high investment, which is depicted by the function's concavity. Owing to the diminishing marginal utility a pure "more is better" approach might not hold true for every amount of investment since it is possible that at a certain point the marginal investment exceeds the resulting marginal cash flow.

c) Resulting Cash Flows: *Cash flow CF_t^s with $s \in \{uu, ud, d\}$ is the sum of cash inflows and outflows at $t \in \{0; 1; 2\}$, resulting from the FM and LM investment. At $t = 2$, it comprises cash flows $CF_j(ep_j^s, B, x)$ with $j \in \{FM, LM\}$ (Cash flows can be interpreted as the present value at $t = 2$ for all possible cash flows generated in the future by the investments):*

$$CF_2^s = CF_{FM}(ep_{FM}^s, B, x) + CF_{LM}(ep_{LM}^s, B, x = 0) - CF_{LM}(ep_{LM}^s, B, x). \qquad 2.$$

Regardless of the point in time, both FM and LM investments belong to the same IT innovation. Therefore, an LM investment reinforces the company's possible FM investment in the IT innovation. As initial investments enable higher marginal cash flows than additional investments, the amount of FM investment, as an initial investment in the emerging IT innovation, must be accounted for when calculating the LM investment's cash flow. Therefore, the cash flow resulting from an LM investment with the invested amount of an FM investment ($CF_{LM}(ep_{LM}^s, B, x)$) is subtracted from the cash flow that would result from an LM investment from the entire budget (i.e., $CF_{LM}(ep_{LM}^s, B, x = 0)$) to calculate the correct cash flow from an investment of the remainder budget as an LM investment (Fig. 2).

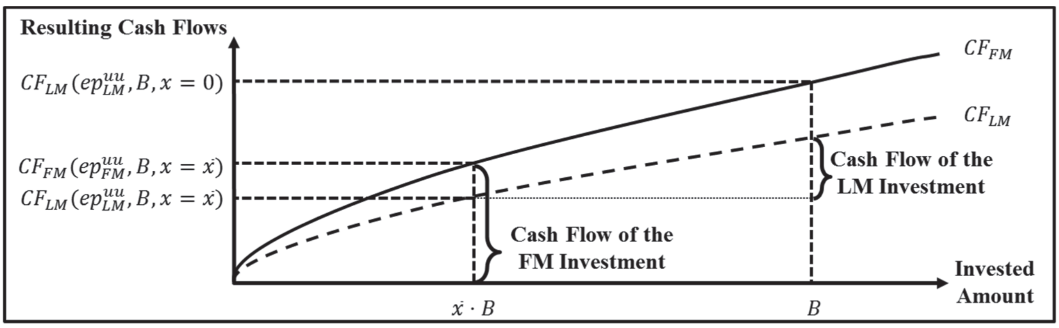

Fig. 2 Resulting cash flows in an upside scenario (illustrative)

In addition to the described IT innovation-related specifics, successful engagement in an emerging IT innovation depends on a company's ability to innovate economically and successfully, that is, the company's innovator profile.

Assumption 4 – Innovativeness of the Company

The cash flows resulting from investments in emerging IT innovation for the upside scenario are multiplied by a company-specific factor $i \in \mathbb{R}^+$, *indicating the company's innovator profile.*

The innovator profile i allows us to consider the company's ability to engage in an IT innovation economically, quickly, and efficiently (Swanson and Ramiller, 2004; Fichman, 2004b). If the company is more innovative, it is generally likely to implement the emerging IT innovation more successfully and generate higher cash flows if the IT innovation becomes institutionalized. The innovator profile reflects a company's innovativeness relative to the market's average innovativeness. Thus, for an average innovative company, $i = 1$; for a below average company, $i < 1$; and for an above average one, $i > 1$. Of course, the impact of the innovator profile only applies to the upside scenario, as a company's individual innovativeness does not matter if the IT innovation fails and vanishes from the market.

The company's possible investments and resulting cash flows for the different scenarios with their associated probabilities are presented in Table 1.

Table 1 Possible scenarios with resulting cash flows and associated probabilities

Scenario	Probabilities	CF_0^s	CF_1^s	CF_2^s
uu	$p_0 \cdot p_1$	$-(x \cdot B)$	$-((1-x) \cdot B)$	$[CF_{FM}(ep_{FM}^{uu}, B, x) + CF_{LM}(ep_{LM}^{uu}, B, x = 0) - CF_{LM}(ep_{LM}^{uu}, B, x)] \cdot i$
ud	$p_0 \cdot (1-p_1)$	$-(x \cdot B)$	$-((1-x) \cdot B)$	$CF_{FM}(ep_{FM}^{ud}, B, x) + CF_{LM}(ep_{LM}^{ud}, B, x = 0) - CF_{LM}(ep_{LM}^{ud}, B, x)$
d	$(1-p_0)$	$-(x \cdot B)$	---	$CF_{FM}(ep_{FM}^{d}, B, x)$

Assumption 5 – Objective Function

The company is a risk-neutral decision maker and aims at maximizing the expected NPV $E[NPV(x)]$ *of the investments in the emerging IT innovation. It is calculated as the sum of expected cash flows* $E[CF_t^s]$ *with* $t \in \{0; 1; 2\}$ *and* $s \in \{uu, ud, d\}$, *discounted with a constant risk-free interest rate* $r \in [0,1]$.

$$\max_x E[NPV(x)] = CF_0^s + \frac{E[CF_1^s]}{1+r} + \frac{E[CF_2^s]}{(1+r)^2}\ s.t. \qquad 3.$$

$x \in [0,1]$; $s \in \{uu, ud, d\}$.

Assume a risk-neutral decision maker is reasonable since investments in new technologies are associated with higher risks than investments that deal with, for example, infrastructure, operational data, and routine processes (Maizlish and Handler, 2005; Ross and Beath, 2002). Therefore, an extensive risk aversion would prevent necessary and useful investments in innovations. The company can maximize the expected NPV by determining the optimal investment strategy indicated by optimal share x^* of the budget ($x = 1$ represents a strict FM strategy, $x = 0$ a strict LM strategy, and $0 < x < 1$ a mixed strategy). A strict FM strategy allows for high cash flows within the upside scenario and bears the risk of rather low or even negative cash flows in the downside scenarios. By contrast, a strict LM strategy possibly results in lower cash flows in the upside scenario or budget saving if the IT innovation is stranded in the first period of development. A mixed strategy, that is, a combination of both strict strategies' chances and risks, possibly leads to a higher expected NPV. The decision is influenced by the amount of strategic budget, success probabilities, and economic potentials of investments regarding the different possible scenarios, and the company's innovator profile.

II.1.4 Model Analysis

In this section, we analyze the model using exemplary applications and sensitivity analyses. First, we analyze different parameter settings (Table 2) depicting the characteristics of possible real-world scenarios regarding the expected NPV and optimal investment strategy. We then examine the impacts of the input parameters on NPV and optimal investment strategy using sensitivity analyses, by changing the values of one parameter, ceteris paribus (Saltelli *et al.*, 2008). Conclusively we derive further insights and illustrate the connection to the assumptions by computing and analyzing its analytical solution.

II.1.4.1.1. Exemplary Application

Table 2 Parameter values for the scenario analyses

Parameter	B	ep_{FM}^{uu}	ep_{LM}^{uu}	ep_{LM}^{ud}	ep_{FM}^{ud}	ep_{FM}^{d}	i	p_0	p_1
Values of baseline scenario	500	1,000	500	0	0	0	1	0.1	0.6
Lower scenario $(.)\downarrow$	250	500	250	-10	-20	-20	0.5	0.1	0.6
Upper scenario $(.)\uparrow$	750	1,500	750	20	10	10	1.5	0.1	0.6

As functions for the expected cash flows, we use standard root functions as they perfectly cover the characteristic of diminishing marginal cash flows (For example the upside scenario's cash flow at $t = 2$ is: $CF_2^{uu} = [ep_{FM}^{uu} \cdot (B \cdot x)^{0.5} + ep_{LM}^{uu} \cdot (B)^{0.5} - ep_{LM}^{uu} \cdot (B \cdot x)^{0.5}] \cdot i.)$.

Expected NPV and Optimal Solution for Different Scenarios: Applying the parameter values of the baseline scenario, the optimal solution, that is, the optimal ex-ante allocation of budget B to the FM and LM strategy is $x = 0.37$. That is, with an investment of 37% ($x^* \approx 0.37$) of the budget at $t = 0$ and saving of 63% for an investment at $t = 1$, the company achieves a maximum expected NPV of 677.99 monetary units (Fig. 3).

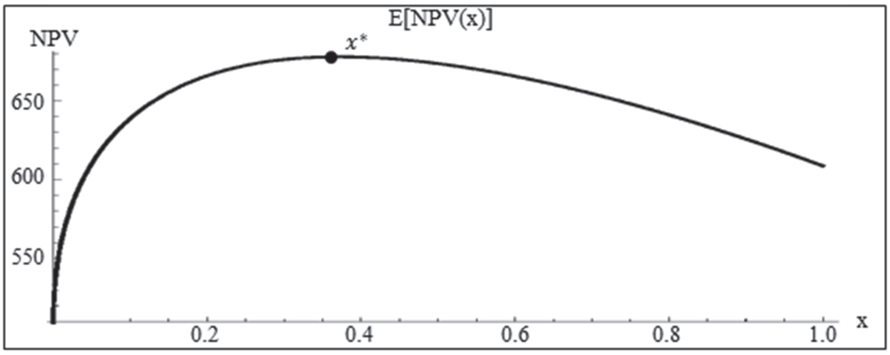

Fig. 3. Expected NPV and optimal solution for the baseline scenario

Fig. 3 indicates that there is one optimal solution. However, the curve's course indicates that a deviation toward the LM strategy is more critical than that of the FM strategy. Thus, the impact of FM advantages over-compensates the impact of the LM strategy's lower risk, that is, the loss of FM advantages due to the reduced allocation toward the FM strategy is more substantial than the reduction of uncertainty. Moreover, compared to a strict FM or LM investment strategy, it becomes rather obvious that a mixed strategy is advantageous as the expected NPV reaches its maximum value.

II.1.4.1.2. Scenario analysis

To further analyze the scenarios, we combine the parameter values of Table 2 that considerably fluctuate around the values of the baseline scenario to cover a broad range of possible scenarios. Since we distinguish between company- and IT innovation-specific input parameters, we combine parameters settings depicting different types of companies and IT innovations. The results are shown in Figure 4.

IT innovation with **high economic potential and risks** $(ep_{FM}^{uu}\uparrow, ep_{LM}^{uu}\uparrow, ep_{FM}^{ud}\downarrow, ep_{LM}^{ud}\downarrow, ep_{FM}^{d}\downarrow)$			
	Company-specific factors	x^*	$E[NPV(x^*)]$
1a	Large budget, above-average innovator profile $(B\uparrow, i\uparrow)$	0.66	1,903.32
2a	Large budget, below-average innovator profile$(B\uparrow, i\downarrow)$	0.01	434.47
3a	Small budget, below-average innovator profile$(B\downarrow, i\downarrow)$	0.01	269.22
4a	Small budget, above-average innovator profile$(B\downarrow, i\uparrow)$	1.00	1,268.42

IT innovation with **low economic potential and risks** $(ep_{FM}^{uu}\downarrow, ep_{LM}^{uu}\downarrow, ep_{FM}^{ud}\uparrow, ep_{LM}^{ud}\uparrow, ep_{FM}^{d}\uparrow)$			
	Company-specific factors	x^*	$E[NPV(x^*)]$
1b	Large budget, above-average innovator profile $(B\uparrow, i\uparrow)$	0.27	640.84
2b	Large budget, below-average innovator profile$(B\uparrow, i\downarrow)$	0.07	168.36
3b	Small budget, below-average innovator profile$(B\downarrow, i\downarrow)$	0.21	134.42
4b	Small budget, above-average innovator profile$(B\downarrow, i\uparrow)$	0.80	463.41

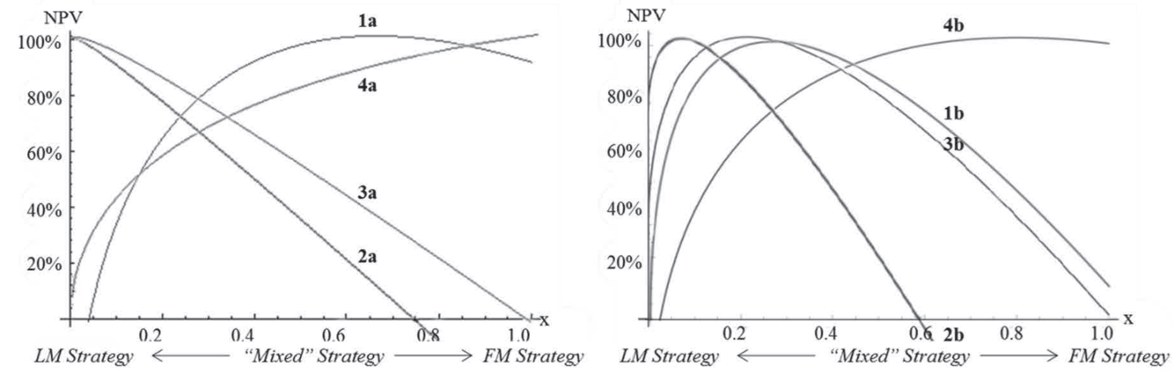

Fig. 4. Overview of results for different scenarios

Regarding company-specific parameters, we assume a company to have a considerably large or small budget and an innovator profile above or below the market average. Furthermore, by varying the IT innovation's economic potentials as IT innovation-specific factors, we cover two interesting IT innovation-related scenarios. First, the emerging IT innovation seems to be a disruptive technology; that is, on the one hand, an engagement bears the possibility of extraordinarily high returns (depicted by choosing the upper limit values for economic potentials in the upside scenario) if the IT innovation becomes institutionalized. On the other hand, it is characterized by the risk of losing more than the budget (depicted by choosing the lower limit values for economic potential in the downside scenarios) if the IT innovation unsuccessfully vanishes from the market (left part of Fig. 4). Second, the IT innovation seems to be a considerable improvement over existing technologies but is not a disruptive technology; that is, on the one hand, it bears the possibility of high, but not exceptional returns (depicted by choosing the lower limit values for economic potentials in the upside scenario) if the IT innovation becomes institutionalized. On the other hand, it is characterized by a lower risk (depicted by choosing the upper limit values for economic potential in the downside scenarios) if the IT innovation unsuccessfully vanishes from the market (right part of Fig. 4). The success probabilities do not vary as they are assumed to be average probabilities that depict the average fraction of IT innovations that become institutionalized, regardless of the IT innovation's possible impact. To test the model's sensitivity for different situations, we combine different company- and IT innovation-related settings, resulting in the different decision situations (Fig. 4).

For a company with a large budget and above-average innovator profile, the optimal investment strategies x^* (0.66 and 0.27) and the related optimal expected NPVs $E[NPV(x^*)]$ ($1{,}903.32$ and 640.84) are rather different. As for the disruptive IT innovation, because of the company's high innovativeness and FM investment's high economic potential for the upside scenario, an allocation of the budget's majority to the FM strategy can be advantageous. Thus, given its high innovativeness, the company can risk acting like a FM to engage in the disruptive IT innovation as it is more likely to be successful and achieve high possible cash flows. In contrast, for the evolutionary IT innovation, a high FM investment is not useful because there are no considerable FM advantages due to the lower economic potential, not even through high innovativeness; therefore, a strategy with focus a on a LM investment is advantageous. However, a higher budget enables deeper engagement and higher cash flows for both IT innovation-specific scenarios compared to the initial situation.

For a company with a large budget but below-average innovativeness, the results significantly differ. Regardless of the IT innovation-specific scenario, the optimal investment strategies x^* (0.01 and 0.07) considerably change toward the LM strategy and the optimal expected NPVs $E[NPV(x^*)]$ (434.47 and 168.36) largely decrease. This shows that below-average companies should rather invest as an LM as they cannot realize the possible FM advantages owing to the lack of knowledge regarding a successful implementation of new technologies. In addition, the expected NPVs show that even a high budget and optimal investment strategy cannot compensate for the disadvantages of low innovativeness. Moreover, the company must invest carefully as the expected NPVs can even be negative for wrongly chosen FM strategies.

In this case, the risk of losing a high budget over-compensates for the possibility of cash flows, which are low owing to the company's inability to successfully adopt new technologies.

Also, changing the budget to a lower limit, indicating a below-average company with few financial funds, compared to the previous scenario, the optimal investment strategy x^* for the disruptive IT innovation is the same (0.01) and marginally changes for the evolutionary IT innovation (0.21). Moreover, the optimal expected NPVs decrease for both types of IT innovations (269.22 and 134.42) owing to the decreased budget. Because of the low innovativeness, the company should rather invest as an LM, especially in the case of disruptive technologies. For evolutionary IT innovation, the company should not completely rely on an LM strategy; rather, it can risk acting like an FM investor and allocate an appropriate share of the budget to FM investments, since the risk within the downside scenarios is considerably lower than that for disruptive IT innovation. Overall, a company with a low budget and below-average innovativeness can reach positive expected NPVs and does not face a high risk of negative NPVs such as the below-average company with a high budget.

Finally, we continue to assume a company with low available financial funds but with above-average innovativeness. As argued, this depicts the situation start-up companies are faced with, as they regularly have lower financial funds available than traditional companies but are often agile and more innovative. An examination situation 4a and 4b (s. Fig. 4) reveals that optimal investment strategies x^* become almost completely reversed (1 and 0.8) and the optimal expected NPVs considerably increase ($1{,}268.42$ and 463.41) compared to the previous analysis. Hence, for both types of IT innovations, strict FM strategies are advantageous, enabling high expected cash flows. In particular, for investments in disruptive IT innovations, small start-ups can monetize possible FM advantages, investing all available financial funds strictly as an FM (taking the risk of possibly going bankrupt). In addition, even for the evolutionary IT innovation, a FM strategy is advantageous, given the lower risk in the downside scenarios and the positive impact of above-average innovativeness on the expected cash flows. Thus, the innovativeness of a company has a considerable positive impact on the optimal investment strategy and expected NPV, even if the company does not have substantial financial resources at its disposal.

II.1.4.1.3. Model analysis conclusions

From the analyses of the initial scenario and different company- and IT innovation-specific scenarios, we draw the following conclusions:

- a below-average innovative company should rather choose an LM strategy;
- an above-average innovative company should rather choose an FM strategy, except if it has a large budget at its disposal and the IT innovation is evolutionary;
- a company with a large budget at its disposal should rather choose an LM strategy, except if it is above-average innovative and the IT innovation is a disruptive one;
- a company with a small budget at its disposal should rather choose an FM strategy if it is above-average innovative and an LM strategy if it is below average;
- as for expected NPV, the impact of the company's innovativeness is stronger than that of the budget; and
- for evolutionary IT innovations, an LM strategy is advantageous, except if the company has a small budget at its disposal and is above average innovative.

Also, the analyses indicate that the optimal investment strategy and the resulting expected NPVs are rather sensitive to different scenarios. Therefore, for the decision regarding the optimal investment strategy, a mindful consideration of company- and IT innovation-specific factors is inevitable.

To enable a better understanding of how the amount of budget influences the decision, we analyzed its isolated impact on the optimal strategy and expected NPV. For the sensitivity analyses, based on the baseline scenario, we show an alteration of the parameter value for budget B. As depicted on the left-hand side of Fig. 5, a higher budget leads to a higher expected NPV and a decreasing share allocated to the FM investment (right-hand side of Fig. 5).

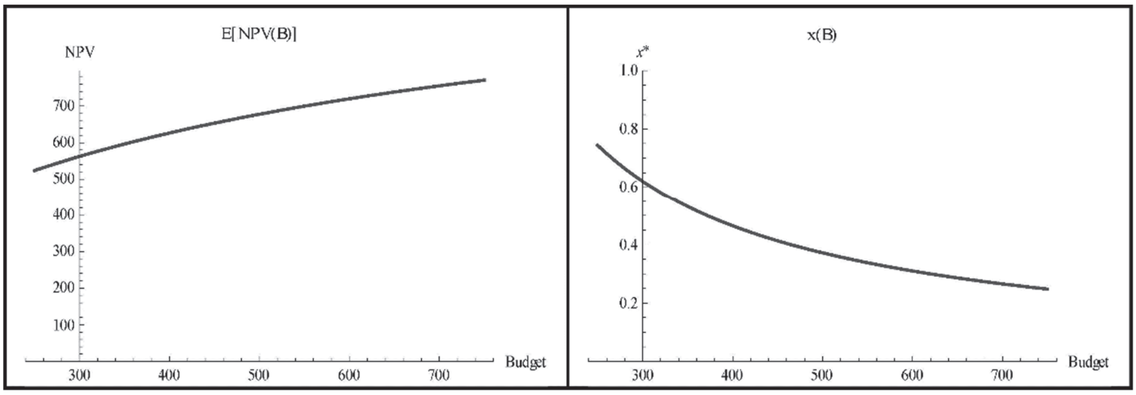

Fig. 5. Influence of budget on expected NPV and optimal solution

The concave increase of the expected NPV demonstrates the cash flows' characteristic of diminishing marginal cash flow; that is, the achievable additional marginal cash flows decrease with an increase in the invested budget. Interestingly, the decreasing allocation to the FM investment indicates that a company with higher financial funds can afford to wait longer, observe the emerging IT innovation's development, and act more as an LM investor. As the budget increases in absolute value, it is possible to save a higher share of the budget for an LM investment without a considerable reduction of the FM investment's amount. Moreover, a company with low available funds would rather invest as an FM investor to maintain the possibility of high cash flows owing to FM advantages.

To derive further insights and illustrate the connection to the assumptions we specified the objective function by inserting all the parameters for different possible scenarios and computed the first derivation of the objective function with respect to x. In sum we can state that for an optimal solution, the risk and return profiles of both investment strategies have to be balanced. Furthermore, increasing one of the economic potential factors of the FM or LM investment strategy should increase the budget share allocated to the respective strategy. An increase in the success probabilities (separately or together) should increase the budget share allocated to the FM strategy; and an increased innovator profile should increase the budget share allocated to the FM strategy.

II.1.5 Conclusions, Limitations, and Suggestions

Decisions regarding a strategy for investments in an emerging IT innovation are often not based on economically well-founded evaluations and analyses, as the market for IT innovations is characterized by intense competition, unclear impacts, and an environment influenced by the hype surrounding an emerging IT innovation. In this context, research can provide valuable insights into the ex-ante determination of optimal investment strategies using quantitative models. In addition to studies analyzing the optimal allocation of recurring IT innovation budgets, it is important to investigate factors affecting decisions regarding optimal strategies for investments in a given emerging IT innovation. To provide insights into causal relationships and analyze key factors, we consider relevant specifics of the company (e.g., budget and innovator profile) and IT innovation (e.g., success probabilities and economic potential) within our quantitative optimization model. By considering these factors, we contribute to central research questions in IT innovation theory, that is, *when* and *to what extent* should a company invest in an emerging IT innovation (Swanson and Ramiller, 2004). As for company-specific factors, first, our analyses show that the amount of available budget positively impacts expected NPV (a higher budget enables higher investments). Second, a higher budget offers a company the opportunity to defer an investment and first observe the IT innovation's development. Therefore, a company with sufficient financial funds does not need to invest its entire budget immediately. Third, the most relevant factor for successful engagement in an emerging IT innovation is the innovativeness of the company. Fourth, broad knowledge and experience regarding how to successfully innovate enables a company to engage in an emerging IT innovation at an early stage and monetize possible FM advantages. Thus, the expected NPV considerably increases, which emphasizes steady organizational learning to improve and maintain a company's innovativeness (Häckel *et al*., 2017). Fifth, our analyses show that even with low financial funds, a remarkable expected NPV can be achieved if the company's ability to innovate is above average. IT innovation-specific factors elucidate that first, for investments in an emerging IT innovation that seems rather evolutionary, an LM strategy is almost always the appropriate investment strategy. Even in this case, a highly innovative company with a low budget should choose a strict FM strategy to monetize FM advantages. Second, far more interesting are rather disruptive emerging IT innovations. Thus, company-specific characteristic, particularly the company's innovativeness, mainly determine the respective optimal strategy and therefore, the risk a company should take. By applying our model to allocate an investment budget, we see that it is advantageous to invest part of our innovation budget in emerging IT innovations, which essentially corresponds to earlier qualitative and empirical studies by Wang (2010), Lu and Ramamurthy (2010) or Dos Santos and Pfeffers (1995). These showed that investments in emerging IT innovations lead to improved company performance. On the other hand, our results show that an LM strategy is meaningful for a below-average innovative company, which supports findings from Hoppe (2000), stating that an LM strategy advantageous, e.g. in the case of a low success probability for an emerging innovation. To reinforce the model's validity and our conclusions, further research in a given organizational context or using empirical data might be valuable (Hevner et al., 2004; Wacker, 1998). Furthermore, our model and its findings may not be practically applicable without adjustments. For example, investments are often not infinitely divisible. Thus, in reality, a possible investment strategy closest to the theoretically optimal solution would have to be chosen. Moreover, further research focusing on some of the limiting aspects might be useful. In particular, the determination of input parameters using empirical and benchmark analyses or educated assessments using experts or consultants and a subsequent analyzation by deep learning methods such as Genetic Algorithm or Neural network algorithm to ensure an expedient data basis could be helpful. A further promising direction for future research could be the development of an integrated portfolio approach that comprehensively depicts investments in different emerging IT innovations. To analyze effects of the real world more precisely, a dynamic multi-period model might be valuable. Such a model could e.g. consider learning effects that reflect the experience a company can gain by a steady and continuous engagement in IT innovations. Despite the model's limitations which offer possibilities for future research, our results and the theoretically sound economic approach contribute to improving a company's decision and further development of a quantitative theory regarding investments in emerging IT innovations.

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II.2 Research Paper 2: "Mindful Engagement in Emerging IT Innovations - A Dynamic Optimization Model Considering Organizational Learning in IT Innovation Investment Evaluation."

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| Published in: | The Data Base for Advances in Information Systems, 48(1), 2017 |

Abstract:

Companies regularly have to decide whether, when, and to what extent to invest in IT innovations with different maturities. Together with mature IT innovations, companies should incorporate emerging IT innovations in their investment strategy. Emerging IT innovations have not yet been widely accepted. Thus, they are characterized by higher uncertainty about their future evolution but have potentially high long-term returns. To enable mindfulness in these decision-making processes, the literature emphasizes organizational learning through continuous engagement in IT innovations to enhance a company's ability to understand, *successfully adopt, and implement emerging IT innovations. IT innovation literature so far has focused on qualitative work, but lacks of quantitative models for the analysis of ex-ante investment decisions. Therefore, we develop a dynamic optimization model that determines the optimal allocation of an IT innovation budget to mature and emerging IT innovations, considering the impact of organizational learning. Based on our model, we examine relevant causal relationships by analyzing the influence of uncertainty, a company's initial individual innovativeness, and the market's average investment share on the optimal engagement. We find that companies should always invest at least a small portion of their budget in emerging IT innovations, regardless of their actual innovativeness. Our results offer new insights into the crucial determinants of investment decisions and provide the basis for future quantitative research on emerging IT innovations.*

II.2.1 Introduction

Driven by market pressure and bandwagon behavior, many companies rush into information technology (IT) innovation investments without sufficient experience. Quite often, these investments turn out to be failing technologies (Lu & Ramamurthy 2010; Swanson & Ramiller 2004). The numerous instances of bankruptcy and failing business models in past crises (such as the dot-com bubble) serve as warning not to engage in IT innovations in a transient hype phase, without carefully considering the questions *whether, when, and to what extent* IT innovations should be adopted.

However, companies never know whether a new technology will be the "next big thing" that guarantees long-term success or whether it will be just a short-term hype that fades away, as was the case with the Wireless Application Protocol (WAP) technology or the HD DVD. We define such *emerging* IT innovations as "technologies that are new on the market and have a low level of adoption, but promise to have high potential". *Mature* IT innovations, in contrast, are technologies that are already widely accepted and institutionalized. Hence, we focus on the phase before a technology crosses the chasm (Moore 1998) from being an emerging IT innovation to becoming a mature IT innovation - a phase when it has the potential to develop into either a lasting technology or a failing one.

Because of their novelty and immaturity, emerging IT innovations "impose significant knowledge barriers that early adopters have to overcome" (Ravichandran & Liu 2011). To overcome these barriers and to enable mindfulness regarding the investments in emerging IT innovations, the literature emphasizes that companies have to "undertake learning to bridge the gap between what they already know and what the new technology requires them to know" (Fichman & Kemerer 1997). Such organizational learning related to the understanding, successful adoption, and implementation of emerging IT innovations is crucial for ensuring long-term competitive advantage and for maintaining a continual level of innovativeness (Wang & Ramiller 2009). To enable sufficient and continuous organizational learning with regard to IT innovations, companies require continuous engagement in such IT experiments (Ross & Beath 2002). This means that a company should regard emerging IT innovations not merely as a flash in the pan but as a persistent share of its innovation strategy. Simultaneously, the company should carefully consider the market's innovation activities in its IT innovation investment strategy to make it difficult for competitors to "replicate [the] company's ability to innovate with IT over the long term" (Stratopoulos & Lim 2010).

Although prior quantitative and qualitative research demonstrated a dependency between organizational learning, IT innovation investments, and the ability to innovate with emerging IT, there is a lack of formal-deductive and mathematical research models that allow the analysis of important causal relationships and the consideration of organizational learning in particular. Williams et al. (2009) demand greater variety in the methodology used in IT adoption and diffusion research to avoid overall homogeneity. To allow companies to gain insights into the relationship involving organizational learning, the company's ability to innovate, and consequently, the level of engagement in emerging IT innovations, we investigate the following research questions (RQs). By answering these research questions, we contribute to the IT innovation literature's overarching research question of *whether, when, and to what extent* companies should engage in emerging IT innovations.

RQ1. *What is a company's optimal IT innovation budget allocation to emerging IT innovations as well as more mature IT innovations?*

RQ2. *How does organizational learning affect a company's optimal IT innovation budget allocation to emerging IT innovations, and how does the investment strategy change over time?*

RQ3. *How do selected company-specific and IT innovation-specific characteristics (e.g., a company's ability to innovate or an IT innovation's chances of success) influence the optimal innovation strategy?*

To investigate these research questions, we follow the basic idea of Meredith et al.'s (1989) research cycle. The authors emphasize that for research areas that have not been thoroughly examined yet, qualitative and mathematical approaches that predict first results provide the basis for generating the hypotheses for future empirical research. Thus, we build on the central findings of IT innovation and organizational learning theory and develop a dynamic n-period optimization model. This model allows us to analyze the crucial causal relationships between a company's ability to innovate, organizational learning, and the optimal allocation of a strategic IT innovation budget to emerging and mature IT innovations. As empirical data in this field is very limited, we apply a simulation-based approach to analyze our model, as suggested by Davis et al. (2007). Such a simulation-based approach allows researchers to provide insights into theoretical relationships in order to gain knowledge about a (largely unexplored) problem domain, thereby helping to solve organizational problems (Davis et al. 2007; Hevner et al. 2004; Peffers et al. 2008; Wacker 1998).

Although we aim to identify and analyze the essential causal relationships that influence IT innovation investment decisions, this study cannot cover the complete decision-making process related to the selection of the “right” IT innovation. Therefore, we concentrate on the challenge of determining the best possible allocation of a periodical IT innovation budget to mature and emerging IT innovations as one basic step of the entire decision-making process and in particular consider the effects of organizational learning. Further steps (e.g., the estimation of an emerging IT innovation’s chances of success) and/or external factors (such as the impact of the success of other companies) are neglected. The rest of this paper is organized as follows. In the following section, we describe the idiosyncrasies of the engagement in emerging IT innovations in further detail and present an overview of the relevant literature. Subsequently, we develop and analyze our model. This serves as the basis for the subsequent discussion of the study’s contributions to research and practice, the possible limitations, and the potential for future research.

II.2.2 Theoretical Background and Related Work

In this section, we first provide an overview of an IT innovation’s lifecycle and link this concept with our definition of emerging IT innovations and their idiosyncrasies. Subsequently, we critically review the extant IT innovation literature to emphasize the importance of distinct research on emerging IT innovations; this line of research is then reviewed critically. We conclude this section by reviewing specific aspects of the organizational learning theory and its relation to a company’s ability to innovate. By discussing these aspects, we lay the theoretical foundation for our formal-deductive mathematical model, which we present in section 3.

II.2.2.1 IT Innovation Lifecycle

Within their lifecycle of adoption (Rogers 2003), IT innovations are often accompanied by waves of both discourse (i.e., rumors) about the innovation as well as its actual diffusion and adoption (i.e., technical implementation) (Abrahamson & Fairchild 1999). Both waves follow a lifecycle that is closely linked to the concept of technology adoption cycles, which was originally proposed by Rogers (2003) and extended into “Hype Cycles” by Gartner Inc. (Fenn & Raskino 2008) from a practitioner’s perspective. This concept illustrates the start of an IT innovation’s lifecycle via a *technology trigger* and excessive publicity, leading to over-enthusiasm and investments based on bandwagon behavior. The hype usually reaches a peak of *inflated expectations* before it fades away in a *trough of disillusionment*. These three milestones mark the phase when an IT innovation can be considered to be "*emerging*" with an unclear destiny (Fenn & Raskino 2008). Therefore, apart from the technological risk that is associated with nearly every type of IT innovation, investments in emerging IT innovations are additionally associated with the risk of investing in a failing technology that will never be institutionalized. After this emerging phase, opportunistic adopters often abandon ship, IT projects are scaled back, and some emerging IT innovations might disappear completely. Only a few technologies are worthy of continued experimentation and solid hard work in order to understand the technology's applicability, its risks, and its benefits, leading to a *slope of enlightenment* for the technology, which is followed by a *plateau of productivity* (Fenn & Raskino 2008).

In the subsequent sub-sections, we show that the extant IT innovation literature tends to neglect the idiosyncrasies of emerging IT innovations. Further, we substantiate why research on emerging IT innovations with a particular focus on the early phase of adoption in combination with organizational learning theory is a valuable contribution to (IT) innovation literature.

II.2.2.2 IT Innovation Literature

While organizational innovation can be broadly defined as "the adoption of an idea or behavior that is new to the organization" (Daft 1978), Swanson (1994) defines IT innovation as "innovations in the organizational application of digital computer and communications technologies (now commonly known as information technology)." IT innovations are important for gaining competitive advantage by becoming more innovative compared to the market average, thus creating an economic value that is unchallenged. McAfee & Brynjolfsson (2008) argue that the speed and effectiveness of innovative IT projects have a major influence on the competitive advantage gained by using IT innovations. It is widely accepted that a set of variables (such as a company's size, structure, or knowledge) affects a company's ability to understand, successfully adopt, and implement IT innovations. Therefore, this can be described as an innovator profile. Companies that fit this profile are expected to innovate more easily, more effectively, and consequently, more economically (Fichman 2004a).

Most traditional research on IT innovation focused on the question "How can companies become innovative by developing their innovator profile?" (Grover et al. 1997; Iacovou et al.

1995). The concentration on a pure "more innovation is better" approach in IT innovation was the result of the so-called pro-innovation bias (Kimberly 1981). This approach assumed innovations per se to be beneficial; consequently, more innovations were assumed to be better. Even though the adoption of IT innovations seems to be beneficial to (Melville et al. 2004) and essential for a company's long-term health (Clark & Guy 1998; Nadler & Tushman 1999), the exclusive investigation of the positive impacts of IT innovations does not seem adequate given that a substantial number of IT innovation projects have failed. Hence, Swanson and Ramiller (2004) as well as Fiol & O'Connor (2003) argue that companies should innovate mindfully, consider the different types of IT innovations, and implement a well-founded IT innovation investment evaluation.

Thus, the analysis of investments in IT innovations should be extended by the questions of *whether, when, and to what extent* emerging IT should be adopted (Swanson & Ramiller 2004). For this purpose, IT innovation research should incorporate other IT innovation-related issues (e.g., probability of institutionalization, ability to innovate properly, learning by doing, impact of the technology, intensity of the market's innovativeness) to depict the complexity of IT innovations more appropriately (Dewan & Mendelson 1998; Fichman 2004b; Rai et al. 2009). Further, Fichman (2003) identified the factors that make companies more prone to adopt IT innovations early because of an IT innovation's expected positive destiny. He states that the conventional IT innovation theory does not consider the expected destiny adequately. By using the term "destiny," he implies that some IT innovations reach institutionalization after crossing the chasm (Moore 1998) of the early phase in adoption, whereas others are abandoned completely or actually never cross the chasm. This unknown destiny makes the evaluation of an engagement in emerging IT innovations an especially challenging task. Therefore, an IT innovation strategy should properly address the idiosyncrasies of IT innovations during the early and middle phases of diffusion and adoption. Hence, we take a closer look at the extant literature that focused on IT innovations in their early stage before developing our model.

II.2.2.3 Literature with a Focus on Emerging IT Innovations

In contrast to traditional IT innovation research, which focuses on the lifecycle phase in which an IT innovation has already been widely accepted and taken for granted (i.e., mature IT innovation), another literature stream focuses on IT innovations during their very early and middle phases of diffusion (i.e., emerging IT innovation). In the very early and middle phases, the long-term destiny of an innovation is unclear; however, an early engagement could lead to first-mover advantage. Unfortunately, companies often tend to adopt emerging IT innovations in the course of an action that is negatively depicted as “bandwagon effect” (Abrahamson 1991; Wang 2010). Some authors such as Fichman (2004a) and Wang (2010) argue that IT fashion theory, as a derivative of management fashions (Abrahamson, 1991), could help to understand the behavior of companies in such an early stage of diffusion and adoption.

As the engagement in emerging IT innovations is usually accompanied by high switching costs (because of the restructuring of the IT infrastructure or tangible artifacts like software and hardware (Fichman 2004a), for example) the required investment should be evaluated very thoroughly. Some prior studies focused on the evaluation of emerging IT innovations and the effects on IT innovation investment strategies. For instance, Dos Santos & Pfeffers (1995) demonstrated the advantages of engagements in emerging IT because of the possibility of adding over-proportional value. Using a game theory approach, Hoppe (2000) showed that under certain conditions, even second-mover strategies could be advantageous because of spillover effects. Lu & Ramamurthy (2010) examined the strategies used in stable and dynamic environments. Their findings generally support the assumption that proactive IT innovation leaders, who regularly engage in emerging IT innovations, outperform reactive IT innovators in terms of overall performance and cost efficiency.

Kauffman & Li (2005) apply a real options approach and argue that technology adopters are better off deferring investments in emerging IT innovations until the technology’s probability of being widely accepted reaches a critical threshold of 60%. However, since determining this specific point in time is a herculean task, the thorough analysis and evaluation of whether, when, and to what extent a company should invest in emerging IT innovations remain important. Wang (2010) found that companies that invested in IT innovations during their hyped or emerging phase gained better reputation and improved their performance because of over-proportional returns resulting from long-term competitive advantages. However, this study does not incorporate the risk of non-institutionalization, provide advice about the extent and timing of investments, or explain how a strategic IT innovation budget should be allocated to different types of IT innovations. However, the consideration of an emerging IT innovation’s risk of failing plays a central role, as later, these investments could either “fail to produce the expected benefits, or indeed, any benefits at all” or “produce some benefits, but not enough to recover the costs of implementation" (Fichman 2004a). Häckel et al. (2013b) explicitly consider the risk of failing (emerging) IT innovations and examine the error that occurs from the so-called fixed strategies regarding investments in IT innovations with different levels of maturity. However, they do not analyze the dynamic changes in the long-term investment strategy caused by organizational learning aspects.

Only very few studies address the long-term effects of the engagement in emerging IT innovations in the context of organizational learning aspects. Stratopoulos & Lim (2010) found that for becoming a systematic innovator who outperforms competitors, persistence and learning regarding the engagement in emerging IT innovation are necessary. Because of continuous learning, systematic innovators have more experience in selecting and implementing IT innovations that are still in a very early phase, as well as in evaluating new applications in the company's context (Swanson & Ramiller 2004). Thus, being successful with such investments is not only linked with the acceptance of the technology by a broad range of companies; further, it also depends on the individual company's ability to innovate with emerging IT innovations, which is described as the innovator profile (Fichman 2004a). For example, Barua & Kriebel (1995) found that companies that are more efficient in utilizing investments in IT are more likely to be aggressive regarding IT investments, and thus, probably also with regard to their engagement in emerging IT innovations. Thus, innovating with emerging IT requires continuous learning to bridge the gap between existing knowledge, experience, and abilities, and the specific aspects of an emerging IT innovation that companies need to know (Fichman & Kemerer 1997; Ke & Wei 2006).

II.2.2.4 Organizational Learning and a Company's Ability to Innovate

Swanson & Ramiller (2004) describe four core phases of the IT innovation engagement, namely, *comprehension*, *adoption*, *implementation,* and *assimilation*. Each phase is linked to different intentions regarding a company's engagement in, commitment to, and achievement from an IT innovation engagement. In the *comprehension phase*, a company has to learn what the IT innovation's intent is, and why it would make sense to adopt the IT innovation. The subsequent *adoption phase* requires a solid assessment of the IT innovation's purpose, benefits, and technical features. Additionally, the business case for the IT innovation has to be evaluated in this phase. Throughout the *implementation phase,* the company has to identify the capabilities required to implement the IT innovation in the company-specific context. Additionally, this phase requires employees' acceptance and training. Moreover, modifications to the innovation may be required in this phase. In the *assimilation phase,* the IT innovation has to be integrated into daily business, and it has to be thoroughly understood to make it productive (Wang & Ramiller 2009).

When dealing with emerging IT innovations (which are characterized by high immaturity and a lack of thorough understanding or best practices), well-founded comprehension, adoption, implementation, and assimilation are challenging tasks. Hence, organizational learning and extensive experience are particularly crucial to the outcome of the engagement in emerging IT innovations. This is because the introduction of emerging technologies imposes "a substantial burden on the adopter in terms of the knowledge needed to understand and use them effectively" (Ke & Wei 2006). The engagement in mature IT innovations also requires experience and benefits from organizational learning. However, a lack of experience in comprehension, adoption, implementation, and/or assimilation regarding mature IT innovations can be compensated largely through existing best practices or the experiences of other companies, for example. Therefore, the organizational learning analysis in this study focuses on the ability to innovate with emerging IT innovations. In this context, organizational learning is defined as an (un)intentional organizational process (for example, through the implementation of successful or unsuccessful projects (Caron et al. 1994)), that makes the acquisition of, the access to, and the revision of organizational memory possible, thereby providing directions for future action (Robey et al. 2000).

Various studies have reported that organizational learning positively affects a company's innovator profile, thereby improving its ability to understand, adopt, and implement IT innovations successfully (Ashworth et al. 2004; Fichman & Kemerer 1997; Salaway 1987; Tippins & Sohi 2003; Wang & Ramiller 2009). Thus, the incorporation of organizational learning into the analysis of investments in emerging IT innovations is very important. Prior research emphasized -either quantitatively or qualitatively -that the learning aspects in an IT innovation engagement, learning through experiments, and persistence in innovating are important for increasing the ability to innovate with IT (Lucas et al. 2008; Stratopoulos & Lim 2010; Swanson & Ramiller 2004; Wang & Ramiller 2009). To measure the outcome of organizational learning, prior organizational and IT innovation research applied learning curves, which describe the development of a company's ability to innovate (Ashworth et al. 2004; Epple et al. 1991; Robey et al. 2000). As learning could result from both negative and positive experience (Caron et al. 1994), it is well accepted that it is important to gain the experience “even if some of that ‘knowledge’ subsequently proves, with growing experience, to be false” (Wang & Ramiller 2009).

The extant quantitative and qualitative literature on organizational learning in IT innovation investments is quite extensive. However, there is a lack of formal-deductive and mathematical research models for analyzing important causal relationships and organizational learning, in particular. As one of the few, Häckel et al. (2013a) consider organizational learning in a mathematical approach; however, they have a rather narrow scope regarding the problem of over-or under-investments resulting from the fixed strategies widely applied in practice. Moreover, Häckel et al. (2015) apply a mathematical approach and focus on the comparison of investment strategies from an ex ante and an ex post perspective by means of a backtesting-approach. The current study considerably extends the work of Häckel et al. (2013a) and Häckel et al. (2015) and aims to address this research gap by incorporating the findings from prior research in a formal-deductive mathematical model and deriving new insights related to IT innovation. In order to gain new insights into the complex theoretical relationships among the various influencing factors, our simulation-based approach aims to provide new theoretical results that can be tested empirically later. Our objective is to analyze how organizational learning affects a company’s investment strategy related to emerging IT innovations over time. Further, we analyze the impact of different company-specific and IT innovation-specific influencing factors, such as an emerging IT innovation’s probability of success or a company’s ability to innovate. These analyses allow us to derive first propositions that build the basis for later research and empirical testing of the described effects, providing further insights for practitioners.

II.2.3 Toward an Optimal IT Innovation Investment Strategy for Emerging IT Innovations Considering Organizational Learning

II.2.3.1 Research Methodology

We apply a two-step approach to answer our research questions, to contribute to academic theory building, and to provide practical guidance regarding the evaluation of IT innovation investment strategies that consider emerging IT innovations and organizational learning. First, we develop a dynamic optimization model that aims to determine the optimal allocation of a periodical IT innovation budget to mature and emerging IT innovations. By considering the domain-specific idiosyncrasies of IT innovation investments, our model can theoretically analyze company-and technology-specific factors that influence the IT innovation budget's optimal allocation.

However, the evaluation of such a model regarding the optimal IT innovation budget allocation is a rather complex and often non-linear problem. Hence, in a second step, we apply a simulation-based approach to identify and analyze important causal relationships. These build the basis for deriving first propositions, which can be tested empirically later. We follow Davis et al. (2007, p. 481), who define a theory as "constructs linked together by propositions that have an underlying coherent logic and related assumptions."

The value of simulation as a methodology for building theory is often questioned, as it may oversimplify reality; thus, it might be too inaccurate to provide thorough theoretical contribution (Chattoe 1998; Davis et al. 2007). However, if applied in an appropriate manner, simulations can serve as powerful tools to gain insights into complex and non-linear theoretical relationships without empirical foundation (Davis et al. 2007; Zott 2003). Therefore, we describe a scenario in which a company is faced with the decision problem of how to allocate an IT innovation portfolio's budget to emerging and mature IT innovation investments. Based on this scenario, we perform multivariate and univariate sensitivity analyses based on a Monte Carlo simulation, which mainly follows the roadmap for developing theory using simulation methods as outlined by Davis et al. (2007). This allows for a comprehensive analysis of theoretical causal relationships with strong internal validity and the illustration of boundary conditions.

However, to strengthen the external validity of our analysis and our first propositions, and for greater generalizability and predictability of our results, further research regarding the evaluation of our model in a specific organizational context or comparison with empirical data might be useful and necessary (Wacker 1998, Campbell & Stanley 1966). For that purpose, we recommend empirical evaluation methods such as case studies, field studies, or statistical sampling to evaluate our approach and theoretical findings (Hevner et al. 2004; Meredith et al. 1989; Wacker 1998). Nevertheless, this sequence of research activities with simulation preceding the empirical validation is closely related to the basic idea of Meredith et al.'s (1989) research cycle. Meredith et al. (1989) highlight the importance of mathematical models for providing first results, which can serve as the basis for future empirical research. Following this approach, in section 6, we explicitly discuss the directions for future research related to our optimization approach, especially regarding the application of additional evaluation methods.

II.2.3.2 Model

The focus of our analysis is the IT innovation portfolio of a company whose strategic IT innovation investments are regularly re-allocated. At every point in time t, the company decides how to allocate a periodical IT innovation budget ($ITIB$) to two different types of IT innovations (*mature* IT innovations vs. *emerging* IT innovations) in order to maximize its expected cash flows over the planning horizon. The investment opportunities are clustered in these two major categories according to their discourse, diffusion, popularity, and maturity (Tsui et al. 2009; Wang 2009).

A) Mature IT innovations: These are IT innovations that have already reached a stage of evolution between the slope of enlightenment and the plateau of productivity according to the concept of hype cycles (Fenn & Raskino 2008) or have already been adopted by a substantial section of the market according to Roger's (2003) theory. Despite institutionalization, mass adoption of these innovations has not been reached yet. Hence, their evolution can be estimated roughly, but the early-mover advantage cannot be realized anymore, as competitive advantage is too low because of their maturity. Examples of mature IT innovations are Customer Relationship Management (CRM), Enterprise Resource Planning (ERP), or Service-oriented Architectures (SOA) (Gartner 2012; Wang 2010).

B) Emerging IT innovations: These IT innovations are in an evolutionary phase between the technology trigger and trough of disillusionment according to the concept of hype cycles (Fenn & Raskino 2008; Wang 2010). Although their long-term evolution is unclear, and substantial adoption is missing, the engagement in this type of IT innovation promises first-mover advantages and, therefore, competitive advantages in case the IT innovation becomes widely accepted and institutionalized later. However, its immaturity impedes reliable estimations about a future evolution, as the hype might fade away before the IT innovation reaches long-term productivity. Based on the current situation of acceptance in research and practice (as of 2015), we can classify IT innovations such as Cloud Computing, Big Data analytic solutions and Near-Field-Communication (NFC) payment technologies as emerging IT innovations (Gartner 2012; Wang 2010).

Since both early-and late-mover strategies related to investments in IT innovations are associated with severe risks as well as tremendous opportunities, companies have to incorporate future developments into their initial evaluation as to how much and when they should invest in which kind of IT innovation (Swanson & Ramiller 2004). To avoid investments that are based on gut feeling, methodically rigorous models that offer a deeper understanding of the problem domain are needed, although they might have to be adjusted to suit the requirements of real-world situations. Therefore, we need assumptions that cover crucial parts of the relevant real-world problem while allowing for a rigorous research model simultaneously.

II.2.3.3 Assumptions and Objective Function

With our model, we aim to cover the essential influencing factors and dependencies that might affect a company's investment strategy regarding emerging or mature IT innovations.

In our model setting, we consider a company that has to decide what share of a given periodical IT innovation budget should be invested in mature or emerging IT innovations to maximize the present value of uncertain cash flows. To make this decision, the company has to consider company-specific influencing factors as well as the peculiarities of the IT innovation investments. Regarding the specifics of the company, in our model, we consider the company's ability to understand, successfully adopt, and implement IT innovations (i.e., the company's innovativeness measured by the innovator profile). In particular, we focus on the fact that a company can improve its ability to innovate with emerging IT innovations via organizational learning. With regard to the IT innovations investments, we distinguish different maturity levels and consider success probabilities as well as the expected market impact (see Figure 1). In this sub-section, we outline the underlying assumptions that describe our model setting in further detail.

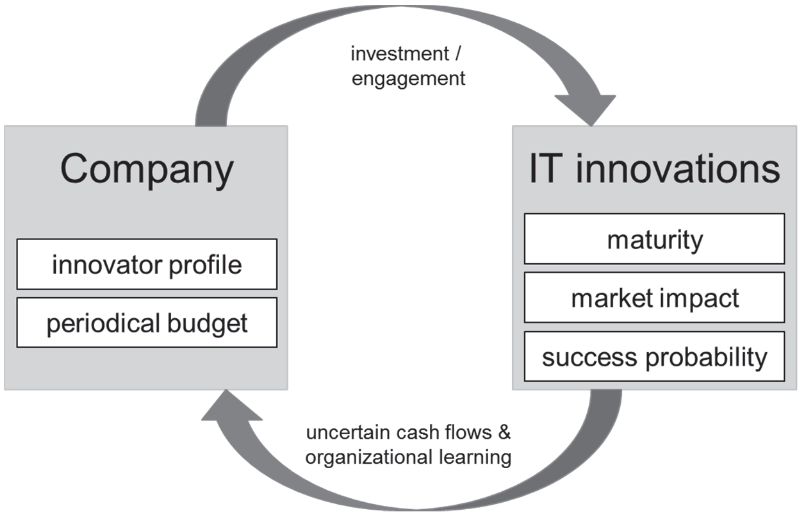

Figure 1. Influencing parameters and effects related to a company's IT innovation investment strategy

Assumption 1: Initial Investment Situation

A company's IT department (in the following discussion, we do not differentiate between the IT department of a company and the company itself) invests a periodical and constant IT innovation budget (ITIB) at specific points in time $t = 0, 1, \dots, n$, each for one period. We define $a_t^E \epsilon [0,1]$ as the share of ITIB that is invested in emerging IT innovations (E) and $a_t^M = 1 - a_t^E \geq 0$ as the share of ITIB that is to be invested in mature IT innovations (M) at t.

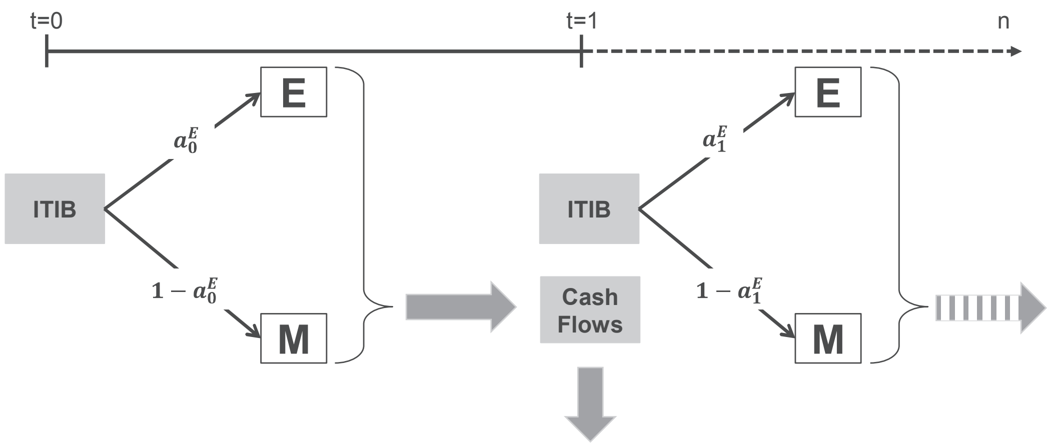

Figure 2. Decision setting over time with $t \, \epsilon \, \{0,1,\dots,n\}$

a) Maturity of IT innovations: The allocation of an IT innovation portfolio's budget to different types of IT innovations follows Ravichandran & Liu's (2011) proposal that a company's IT investment strategy refers to its "strategic orientation toward IT investing in terms of scale and proactiveness." Thus, we model the scale in terms of the share allocated to mature and emerging IT innovations. Additionally, and even more importantly for our scope, we consider proactiveness in terms of a company's "attitude toward technology adoption" (Ravichandran & Liu 2011, p. 542) by differentiating between IT innovations with different maturities and potential risks. Figure 2 presents the split of $ITIB$ into the two investment alternatives, E and M.

b) IT innovation lifecycle: There is a steady flow of IT innovations newly appearing on the horizon and IT innovations at a higher maturity level. Therefore, our model describes the recurring decision situation of a company that regularly (i.e., in each period) has to decide about the allocation of its IT innovation budget to IT innovations with different degrees of maturity. Each period of the planning horizon represents the time frame between the point in time when an emerging IT innovation appears (i.e., the technology trigger, peak of inflated expectations, and trough of disillusionment) and the point in time when its destiny becomes clear (slope of enlightenment with institutionalization or failure). Breaking an IT innovation's lifecycle down into a recurring time frame with one period definitely simplifies the matter, but it allows us to analyze a longer time frame of subsequent decisions regarding the allocation to mature and emerging IT innovations. Thus, we analyze a company's IT innovation strategy over a longer time frame, and for each recurring decision situation, we focus on the essential phase in which the destiny of an emerging IT innovation becomes apparent (Wang 2010).

Assumption 2: Portfolio Perspective

The IT innovation portfolio's cash flows CF_t^{PF} consist of the cash flow from the investment in an emerging IT innovation CF_t^E and the cash flow from the investment in a mature IT innovation CF_t^M.

$$CF_t^{PF} = CF_t^E + CF_t^M \text{ with } t \in \{1,2,\dots,n\}$$

Consequently, the investment alternatives E and M generate specific cash flows that depend on the emerging IT innovation's (E) uncertain destiny of becoming institutionalized as well as the mature IT innovation's (M) success in the market. To model the idiosyncrasies of the decision setting in more detail, we take a closer look at the cash flows that are realized by E and M.

Assumption 3: Achievable Cash Flows

The cash flows CF_t^E and CF_t^M resulting from the investments in E and M, respectively follow a strictly monotonically increasing, concave function, which is differentiable twice and depends on the IT innovation budget's share a_{t-1}^i with $i \in \{E, M\}$ that was allocated to E and M in the previous period $t-1$:

$$CF_t^i(a_{t-1}^i) = \left(a_{t-1}^i \cdot ITIB\right)^{q_z^i} \cdot v_{t-1}^i$$

where $i \in \{E, M\}$ and $t \in \{1,2, \ldots, n\}$. Thereby, $q_z^i \in [0,1)$ describes the technology-specific impact factor depending on the realized scenario $z \in \{u, d\}$, and $v_{t-1}^i \in \mathbb{R}^+$ describes the company's individual innovator profile for the IT innovations $i \in \{E, M\}$.

a) Basic shape of the cash flow functions: Monotonically increasing cash flow functions are reasonable since a higher investment in and commitment to an IT innovation generally enable a deeper engagement in and a broader implementation of the technology. Thus, there are more opportunities to create value from the investment later (Fichman 2004b; Kimberly 1981; Melville et al. 2004). Further, we can argue that an increasing investment in E or M is characterized by a diminishing marginal utility regarding $CF_t^i\left(a_{t-1}^i\right)$, i.e., $\partial^2(CF_t^i(a_{t-1}^i))/\partial^2 a_{t-1}^i < 0$, according to production theory (Varian 1999). The initial engagement in IT innovation creates more value than an incremental increase of an already high investment, since companies need a reasonably high initial engagement to enter a market or become reasonably familiar with a technology (Lu & Ramamurthy 2010; Stratopoulos & Lim 2010). Thus, a pure "more is better" approach might not hold true for every IT innovation investment. Further, for both scenarios (downside as well as upside), it is possible that the invested share of the budget $a_{t-1}^i \cdot ITIB$ exceeds the resulting cash flows $CF_t^i(a_{t-1}^i)$ because of diminishing marginal utility. This would result in a loss for the company. This also applies for the complete IT innovation portfolio, since the invested budget could exceed the cash flows resulting from the investment in mature and emerging IT innovations.

b) Impact of the technology: The factor $q_z^i \in \{q_u^E, q_u^M, q_d^M\}$ that is constant over time can be interpreted as a technology-specific impact factor, which describes the degree of impact of E and M *depending on the realized scenario* $z \in \{u, d\}$. This includes the IT innovation's acceptance by customers or employees, its stability, and the probability of an easy integration into the company's existing IT infrastructure, all of which influence the investment's cash flow (Fichman 2004b; Haner 2002; Moser 2011). If emerging IT innovations are institutionalized and accepted by the market, they would usually have a higher impact, thereby generating higher cash flows for the company (Lu & Ramamurthy 2010; Wang 2010). Therefore, we assume that E's impact factor is higher than M's for the upside scenario. For the downside scenario, we assume that the mature IT innovation still has a positive impact; however, it is lower than that for the upside scenario. We assume that the emerging IT innovation would completely fade away in a downside scenario without any impact; therefore, it would not generate any cash flows. As an IT innovation's impact on the market is difficult to predict, both scenarios have to be considered, i.e., a high impact ("upside" with $z = u$) and a low impact ("downside" with $z = d$) (Fenn & Raskino 2008; Moser 2011). Therefore, we model an upside scenario as well as a downside scenario for M and E, thereby incorporating the possibility of a positive or negative outcome.

c) Innovativeness of the company: The factor $v_{t-1}^{i} \epsilon \mathbb{R}^{+}$ with $i \epsilon \{E, M\}$ can be interpreted as the company's individual innovator profile at t with regard to mature or emerging IT investments. Hence, this factor describes the company's ability to engage in an IT innovation economically, quickly, and efficiently (Fichman 2004a; Swanson & Ramiller 2004), i.e., its ability to innovate. To allow for an easier interpretation of the innovator profile v_t^i with $i \epsilon \{E, M\}$, we denote a company that is on average or opportunistically innovative (compared to the market) at t with $v_t^{i^*} \epsilon \mathbb{R}^{+}$, below average innovative companies with $v_t^i < v_t^{i^*}$, and first and progressive movers with $v_t^i > v_t^{i^*}$. Thus, in our approach, the individual innovator profile always depicts a company's innovativeness in comparison to the market average. In doing so, we adapt the empirical findings reported by Stratopoulos & Lim (2010) and Lu & Ramamurthy (2010) into our analytical model.

In this context, a company can improve its individual position compared to the market through a steady engagement in IT innovations. The extant literature (e.g., Nagji & Tuff 2012; Stratopoulos & Lim 2010; Wang & Ramiller 2009) emphasizes the fact that steady engagement in *emerging* IT is important for a company's continuous innovativeness and for continuous learning. Further, the literature argues that *experiments* are the main source of transformational innovation. Therefore, our analysis of organizational learning focuses on the engagement in *emerging IT innovations.* This focus is reasonable as in contrast to mature

IT innovations, emerging IT innovations require a substantially higher level of experience in comprehending, adopting, implementing, and assimilating new IT because of their immaturity and the lack of thorough understanding and best practices (see section 2.4). Consequently, we narrow our analysis to the effects of organizational learning on the company's individual innovator profile related to emerging IT innovations v_t^E. For reasons of simplicity, we assume that the individual innovator profile related to mature IT investments v_t^M is constant over time.

Assumption 4: Organizational Learning

The development of a company's individual innovator profile related to *emerging IT investments v_t^E follows a learning curve in the form of an s-curve, which depends on a_{t-1}^E:*

$$v_t^E = v_{t-1}^E \cdot S_{t-1}(a_{t-1}^E)$$

$$= v_{t-1}^E \cdot \left((1-\beta) + \frac{2 \cdot \beta}{1 + \exp\left(-k \cdot (a_{t-1}^E - \alpha^E)\right)} \right)$$

with a periodical increase or decrease in the innovator profile$S_{t-1}(a_{t-1}^E)$, the maximal growth rate β, the market's average engagement α^E, and a proportionality factor k.

a) Learning curve: Learning curves constitute a widely applied and accepted subject in IT innovation literature (Robey et al. 2000; Ashworth et al. 2004). There are different ways of modeling the increase in knowledge over time. For instance, Wang & Ramiller (2009) focus on community learning. In this study, we model a *learning-by-doing* (i.e., engagement in emerging IT innovations) relation. This is analogous to approaches where the required labor for production decreases with an increase in production (Epple et al. 1991). Therefore, we model the development of a company's individual innovator profile related to emerging IT innovations in the form of an s-curve (Kemerer 1992; Raccoon 1996), as this is the most suitable curve for depicting the increasing but somehow limited ability to innovate with IT. Our specific learning curve is based on the well-known logistic function and is adjusted to our particular requirements. In this context, the value generated by the applied s-curve depicts the periodical increase or decrease in the innovator profile. The s-curve itself does not represent a company's ability to innovate. Instead, as the formula shows, $S_{t-1}(a_{t-1}^E)$ is just a multiple, which depicts the difference between the company's innovator profile at $t-1$ and t. It reflects the periodical impact of organizational learning on the innovator profile; thus, this curve helps to describe the development of the innovator profile over time.

b) Market's average engagement in emerging IT Innovations: As we measure v_t^E in comparison to the market average, the included shift assumes a competition-based, relative learning effect that depends on the market's average engagement in emerging IT innovations α^E. This implies that a company can increase its innovator profile related to emerging IT investments relative to the market only if it invests in emerging IT more than the market's average does, i.e., $a_{t-1}^E > \alpha^E$. Consequently, the company's individual innovator profile decreases relative to the market if its engagement is lower than the market average α^E, although in absolute terms, the company might realize organizational learning through its engagement in emerging IT innovations. It is important to note that we assume an exogenous market. Thus, we do not model the dynamic investment behavior of competitors or the interdependencies between the investment strategies of market participants. For that reason, we do also not consider how the market's average engagement develops over time. Consequently, our research focuses on analyzing the investment strategy of a single company given an exogenous market with a certain average level of engagement in emerging IT innovations.

c) The course of the learning curve: The growth rate β specifies the maximal periodical increase (or decrease) in the innovator profile generated by the learning effect. The proportionality factor k is an indicator of how sharply the curve increases; therefore, it indicates how strongly the difference between the company's investment level and the market average influences the learning effect. For low values of k (e.g., $k = 5$), a very high investment share of nearly 100% is necessary to reach the maximal periodical learning effect. For high values (e.g., $k = 30$), even a small deviation from the market average would lead to a maximal increase/decrease in the learning effect. Thus, the learning curve depends on the extent of the engagement in emerging IT innovations, regardless of whether they will be successful (Caron et al. 1994). In addition to the learning curve, we restrict the company's innovator profile to a global upper limit. This means that an innovative company would reach a level of saturation at some point in time, which would impede its possibility to become infinitely more innovative than the market average. Since we assume an exogenous market, we do not consider the development of the competitors' innovativeness over time. Thus, we also do not depict the possibility that the average innovativeness of the competitors converges to some upper limit.

Assumption 5: Uncertainty

Uncertainty about the mature and emerging IT innovation's possible outcome and, consequently, the risk of undesirable outcomes are described by the probability p^i *for the upside scenarios and* $(1 - p^i)$ *for downside scenarios, with* $i \in \{E, M\}$ *via a binomial distribution.*

a) Success probabilities: p^i with $i \in \{E, M\}$ describes the possibility that an investment in E or M at $t + 1$ creates the desired cash flows (E^u or M^u). Using $1 - p^i$, we describe the probability that an investment in E or M would create below-average or zero cash flows (E^d or M^d). Figure 3 illustrates the different possible scenarios related to the development of E and M and the probabilities for the scenarios.

Though different emerging IT innovations are likely to be characterized by different probabilities regarding institutionalization in reality, for reasons of simplicity, we assume the probability p^i with $i \in \{E, M\}$ to be constant over time. This is justifiable as constant probabilities do not disturb the general results of our model, and varying probabilities might only appear to improve the accuracy of measurement.

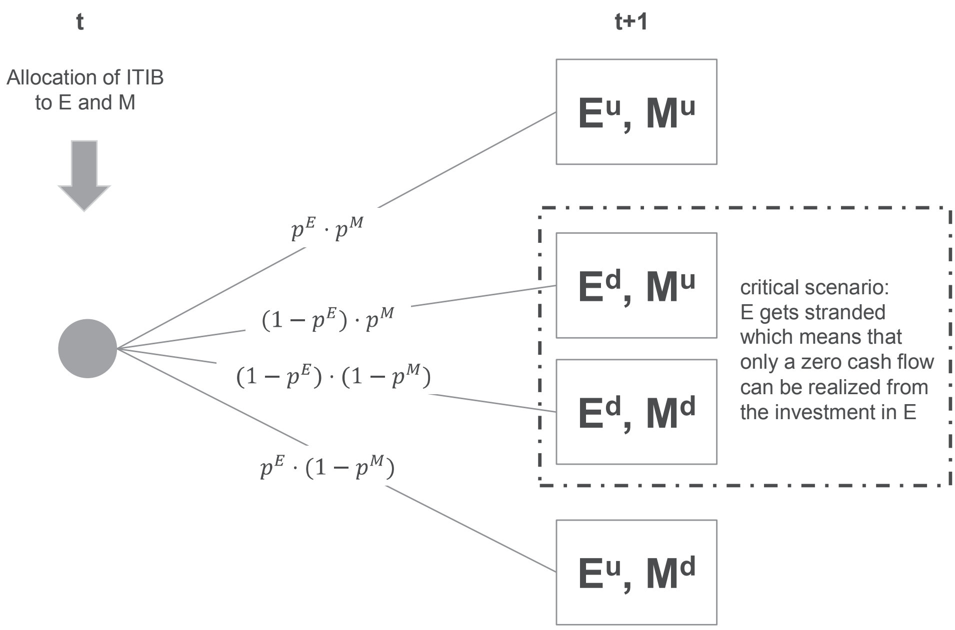

Figure 3. Scenarios for the development of the IT innovations E and M at t and $t + 1$

b) Upside and downside scenario: An emerging IT innovation could turn out to be either a failing technology (i.e., a downside scenario leading to zero cash flows at $t + 1$) or a groundbreaking technology (i.e., an upside scenario with q_u^E resulting in extraordinary high cash flows for early movers). Therefore, its cash flow at $t+1$, after the hype around the technology has waned, is of particular interest to us (Fenn & Raskino 2008; Fichman 2004b; Moser 2011). Regarding the mature IT innovation, we also have to consider a downside as well as an upside scenario. According to our assumptions, investing in E or M at t could result in the cash flows CF_{t+1}^E or CF_{t+1}^M at $t+1$, as shown in Table 1.

Table 1. Scenarios for the IT innovation's cash flows

		$t+1$
Upside scenario (p^i) with $i \in \{E, M\}$	E	$(a_t^E \cdot ITIB)^{q_u^E}$
	M	$(a_t^M \cdot ITIB)^{q_u^M}$
Downside scenario ($1-p^i$) with $i \in \{E, M\}$	E	0
	M	$(a_t^M \cdot ITIB)^{q_d^M}$

Assumption 6: Objective Function

The company is a risk-neutral decision maker that aims to maximize the net present value (NPV) of the IT innovation portfolio's expected cash flows. The expected cash flows are discounted to the present with a risk-free interest rate $r \in [0,1]$, *which is assumed to be constant for each period.*

a) Risk neutrality: Assuming a risk-neutral decision maker for the investment decisions regarding a company's IT innovation portfolio is reasonable, as the IT innovation portfolio's scope is to perform basis research for discovering long-term value. Hence, an IT innovation portfolio, by definition, deals with riskier investments compared to an IT asset portfolio, which deals with infrastructure, operational data, and routine processes, for example (Maizlish & Handler 2005; Ross & Beath 2002).

b) Objective function: As the company has to decide how to allocate its IT innovation budget $ITIB$ at t, it aims at an ex ante decision regarding the allocation of $ITIB$ that maximizes the IT innovation portfolio's expected NPV. This leads to an objective function of the dynamic optimization problem in the following form:

$$\max_{a_t^E} \sum_{t=0}^{n} \frac{-ITIB + E(CF_t^{PF})}{(1+r)^t} \; s.t.$$

$$0 \leq a_t^E \leq 1$$

$$v_t^E = v_{t-1}^E \cdot S_{t-1}(a_{t-1}^E)$$

After describing the model with the possible scenarios, cash flows for different periods, and the objective function, we evaluate and analyze the model in the subsequent section. Table 2 summarizes the major parameters of the model.

Table 2. Summary of major parameters

Parameter	Description
$ITIB$	Periodical strategic IT innovation budget
a_t^E	Share of $ITIB$ that is invested in emerging IT innovation at t
a_t^M	Share of $ITIB$ that is invested in mature IT innovation at t
v_t^E	Company's individual innovator profile related to emerging IT investments at t
v_t^M	Company's individual innovator profile related to mature IT investments at t
q_u^E	Emerging IT innovation's impact factor in case of high market impact (upside scenario)
q_u^M	Mature IT innovation's impact factor in case of high market impact (upside scenario)
q_d^M	Mature IT innovation's impact factor in case of low market impact (downside scenario)
p^E	Probability that emerging IT innovation will be institutionalized
p^M	Probability that mature IT innovation will create desirable cash flows
α^E	Average investment share in emerging IT innovation of the market
k	Proportionality factor for learning effect
β	Maximal periodical learning effect on innovator profile
G	Global upper limit for innovator profile indicator

II.2.4 Model Analysis

To solve this dynamic optimization problem (dynamic programming according to Bellman (1957)), we build on the decision tree that is determined by the scenarios described in Figure 3. To analyze the decision tree with the different scenarios regarding the evolution of E and M, we apply a roll-back approach (Clemons & Weber 1990; Magee 1964; Tufekci 1993). A major advantage of this decision tree-based roll-back analysis is that its primary focus is on the investment decisions that have to be made, the incorporation of the interrelationships between the variables, and the global optimization over the possible decisions (Bonini 1975).

II.2.4.1 Methodological Approach

To apply the roll-back approach, we initiate the optimization problem with an "arbitrary" initial allocation - in our case, with the market's average investment share in the emerging IT innovation α^E for every point in time t (see first row of Figure 4). In the first step of the roll-back optimization for a 10-period model, we start with the last decision point and determine the "conditionally" optimal share $\hat{a}_9^E$ for $ITIB$ at $t = 9$, such that the cash flow at $t = 10$ is maximized.

All previous cash flows do not have to be considered in the roll-back approach, as they do not vary with a change in $\hat{a}_9^E$; therefore, they do not affect the conditionally optimal solution. Thus, the share $\hat{a}_9^E$ is only conditionally optimal, as the other parameters are still "arbitrary." In the second step, the company determines the conditionally optimal share at $t = 8$ by taking the conditionally optimal share for $t = 9$ into consideration (the share $\hat{a}_9^E$ is not varied in this step) and maximizing the cash flows at $t = 9$ and $t = 10$, leading to $\hat{a}_8^E$. The cash flow at $t = 10$ needs to be included as the determination of $\hat{a}_8^E$ affects the innovator profile v_9^E, and therefore, the cash flow at $t = 10$. This procedure is repeated until $\hat{a}_0^E$ is determined. This share is assumed to be unconditionally optimal, as all subsequent $\hat{a}_t^E$ are already (conditionally) optimized. Consequently, we name it $a_0^{E^*}$. Subsequently, $ITIB$ is re-allocated at $t = 1$ based on the altered v_1^E that results from the organizational learning effect depending on the optimal engagement $a_0^{E^*}$ in emerging IT at $t = 0$ (see rows 6-7 in Figure 4). The optimization is repeated, and the (conditionally optimal) IT innovation strategy for $t = 2, \ldots, 9$

is possibly re-allocated according to the scenarios and the organizational learning effect that is realized.

Since this heuristic approach only converges to the unique globally optimal solution, further iterations of the roll-back approach would be necessary to guarantee an (sufficiently precise) optimal solution. However, as the results changed only negligibly with a second, third, and fourth iteration in a variety of tests, while the computational time required increased significantly, we apply a single-iteration implementation in this study.

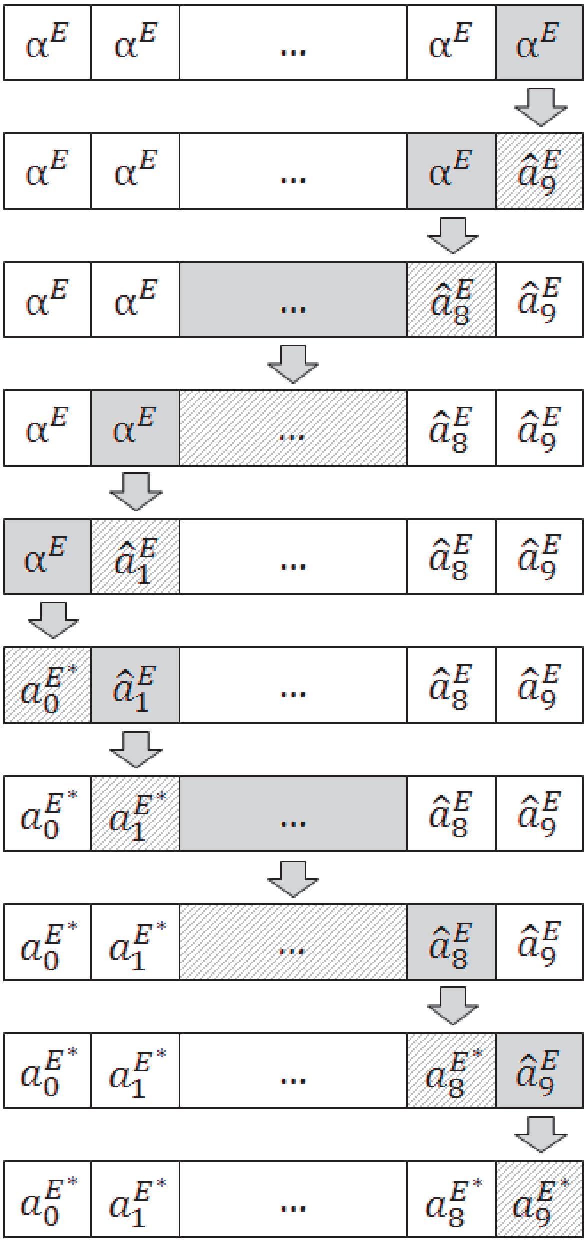

Figure 4. Schematic representation of the roll-back approach for the sequential solution of the multidimensional, dynamic optimization problem

In addition to the decision tree analysis, a real options approach, as applied by Kauffman and Li (2005), Fichman (2004b), and Benaroch (2002), would be suitable for addressing the presented decision setting. The investment in an emerging IT innovation could be interpreted as an option that provides the possibility to establish a new business model later. However, the real options approach aims at valuating the future flexibility enabled by a strategic investment; it does not support the ex ante allocation of an IT innovation budget to mature and emerging IT innovations. Additionally, a real options approach requires restrictive assumptions such as adequate twin security for calculating state-contingent values. In the case of IT innovations, it is particularly difficult to find a twin security that is priced in active trading and that has payouts that are perfectly correlated with an emerging IT innovation. Finally, real options always have a positive or zero value (Copeland et al. 2005). In the case of investments in emerging IT innovations, even negative values for the investment have to be considered, which makes a real option analysis rather difficult.

It is virtually impossible to obtain real-world data for an in-depth examination of the benefits of our theoretical approach since companies often lack thorough, well-defined decision-making processes. Nevertheless, as stated in the subsequent sub-sections, considerable advantages can be realized by incorporating the results obtained by using the model to make decisions as to whether, when, and to what extent a company should engage in emerging IT innovations. The focus of this study is to illustrate and analyze the important causal relationships involving the factors that influence IT innovation investment decisions rather than to apply an approach that provides specific guidelines or recommendations for decision support.

II.2.4.2 Structure of the Analyses

To derive first insights about the model, its functionality, and the resulting investment strategy, we choose one initial parameterization of the model (see the initial values in Table 3) and analyze the optimal allocation for this concrete scenario in section 4.3. Subsequently, to derive results and hypotheses in a more general setting, we conduct multivariate sensitivity analyses for a 5-period, a 10-period, and a 20-period model by randomly changing *all* the parameters of major influence using a Monte Carlo simulation. By means of the Monte Carlo simulation we can generate a large number of arbitrary chosen parameter settings for the analyses, covering a wide range of possible investment scenarios. Based on the multivariate sensitivity analyses, we are able to demonstrate the model's sensitivity in terms of a broad spectrum of different parameter settings. In particular, we can analyze the frequency distribution as well as the range of the optimal allocations, and how they vary for different planning horizons. In addition to the mean value of the optimal allocation, we can observe which extreme values could occur for the best-case and the worst-case parameter settings. Finally, we analyze several important model parameters (uncertainty, company's initial individual innovator profile related to emerging IT investments, average market investment share) individually and examine their influence on the optimal allocation. For this, we conduct a univariate sensitivity analysis for each parameter and analyze a minor number of scenarios by changing the values of the parameters, ceteris paribus. Thus, the changes in the model's output can be "apportioned to different sources of uncertainty in the model input" (Saltelli et al. 2008).

Table 3 presents the simulation's initial values and their ranges. The values in Table 3 serve as the starting point for all the analyses. The initial values are held constant in the univariate sensitivity analyses, except those parameters that are subject to each analysis. For the sake of simplicity, we assume equal distributions for all the parameters, as other distributions (such as the Gaussian distribution) would not distort the general conclusions, but would increase complexity. Analogous to Kauffman & Li (2005), we consider $r = 0.1$ for the risk-free interest rate. Further, we start with $v_t^{M^*} = 100$ for the company's individual innovator profile related to mature investments. We generally start our analyses with rather conservative values. Further, we range the relevant parameters in conservative intervals to avoid distortion because of overoptimistic value estimations.

To demonstrate the impact of organizational learning on investment decisions related to emerging IT innovations, our univariate sensitivity analyses always include a comparison between the optimal IT innovation budget allocation resulting from the model *with learning effect* and that from the model *without learning effect*. In this regard, the model without learning effect is no longer a dynamic optimization problem leading to a constant optimal engagement over time.

Table 3. Data for the Monte Carlo simulation and the analyses

Parameter	Initial Value	Range
Company's individual innovator profile indicator v_0^E	100 ($= v_t^{E^*}$)	70 – 110
Emerging IT innovation's impact factor q_u^E (upside scenario)	0.40	0.20 – 0.50
Mature IT innovation's impact factor q_u^M (upside scenario)	0.35	0.15 – 0.40
Mature IT innovation's impact factor q_d^M (downside scenario)	0.15	0.01 – 0.20
Probability p^E that emerging IT innovation gets institutionalized	0.10	0.01 – 0.20
Probability p^M that mature IT innovation gets institutionalized	0.20	0.20 – 0.35
Average investment share of the market α^E	0.05	0.01 – 0.25
Proportionality factor for organizational learning k	10	5 – 30
Maximal periodical organizational learning effect on innovator profile β	0.15	0.05 – 0.20
Global upper limit G for the company's innovator profile	250	150 – 250

II.2.4.3 Analysis of the Optimal Allocation for Initial Values

In our first analysis, we examine the optimal allocation of the IT innovation budget $ITIB$ to E and M for a company in a specific investment scenario with a planning horizon of 10 periods. We calculate the optimal allocation for the case where the model is parameterized with the initial values from Table 3 and show the results for the 10 decision points in Figure 5. At the beginning of the planning horizon at $t = 0$, the optimal allocation suggests the investment of a share of 40.5% in E and 59.5% in M. Instead of keeping this investment ratio constant over time, Figure 5 clearly shows that because of organizational learning and the growing ability to understand, successfully adopt, and implement emerging IT innovations, the optimal allocation changes over time. In this scenario, the engagement in E slightly increases up to

59.4% at $t = 7$. Interestingly, the optimal allocation does not change anymore at $t = 8$ and $t = 9$. The innovator profile for this scenario shows that the company reached the global upper limit G of innovativeness; therefore, the engagement levels off at a constant investment share. However, this result applies only for the chosen parameterization and does not allow for generalization. In order to derive more meaningful propositions, we conduct further multivariate sensitivity analyses by varying all the relevant parameters using a Monte Carlo simulation in the following sub-section.

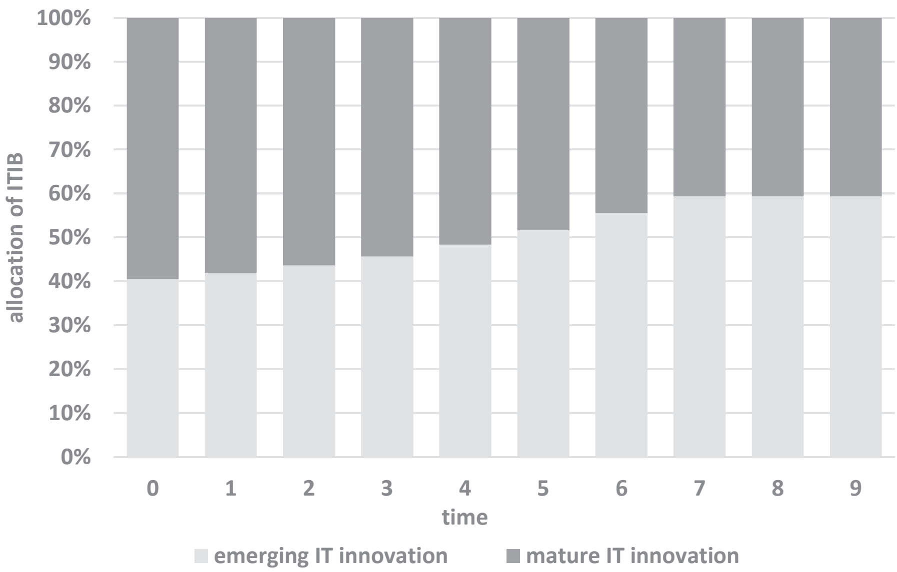

Figure 5. Optimal allocation of the IT innovation budget $ITIB$ to emerging and mature IT innovations over time

II.2.4.4 Multivariate Sensitivity Analyses of the Optimal Allocation

Simulating all the parameters allows us to gain deeper insights into the optimal investment strategy and the causal relationships. The planning horizon considered for the analysis plays an important role for organizational learning, as a potential increase or decrease in the innovator profile would affect future investments and the resulting cash flows. Thus, we conduct the Monte Carlo simulation for a 5-period, a 10-period, and a 20-period model. In our simulation for the 5-period model, we randomly generate 5,000 parameter settings and calculate the optimal allocation for each parameter setting. With an increasing planning horizon of 10 (and 20) periods, the calculations require additional computational runtime. Since our analyses reveal that the results change only very slightly with an increasing number of parameter settings while increasing the runtime of the simulation disproportionally, we simulated 3,000 scenarios for the 10-period model and 1,000 scenarios for the 20-period model. These sample sizes, however, should be large enough to ensure reliable results for our analyses.

Because of the large number of possible constellations related to the influencing parameters, for the 5-period model, the optimal allocation share $a_t^{E^*}$ (considering all the points in time t) ranges from a minimum of 1.7% to a maximum of 85.3%, with an overall mean value of 37.2%. The upper limits of $a_t^{E^*}$ for the 10-period and 20-period models are comparably high. However, the lower limit of $a_t^{E^*}$ for the 20-period model increases substantially to a comparatively high value (15.2%) compared to that of the 10-period model (see Figure 6). This can be explained by the fact that even in the "worst-case scenarios" (given a parameterization that implies less profitable investments in E than in M, and therefore implies a low engagement in E), the engagement could be beneficial to a certain extent, as the involved learning effect pays off in later investments. Hence, organizational learning considerably affects the development of the optimal engagement in E over time. The average engagement of 37.2%, 46.2%, and 50.0% increases with the planning horizon, as the learning effect encourages a company to invest substantially in E in order to increase the long-term innovator profile and, consequently, the benefit in later periods.

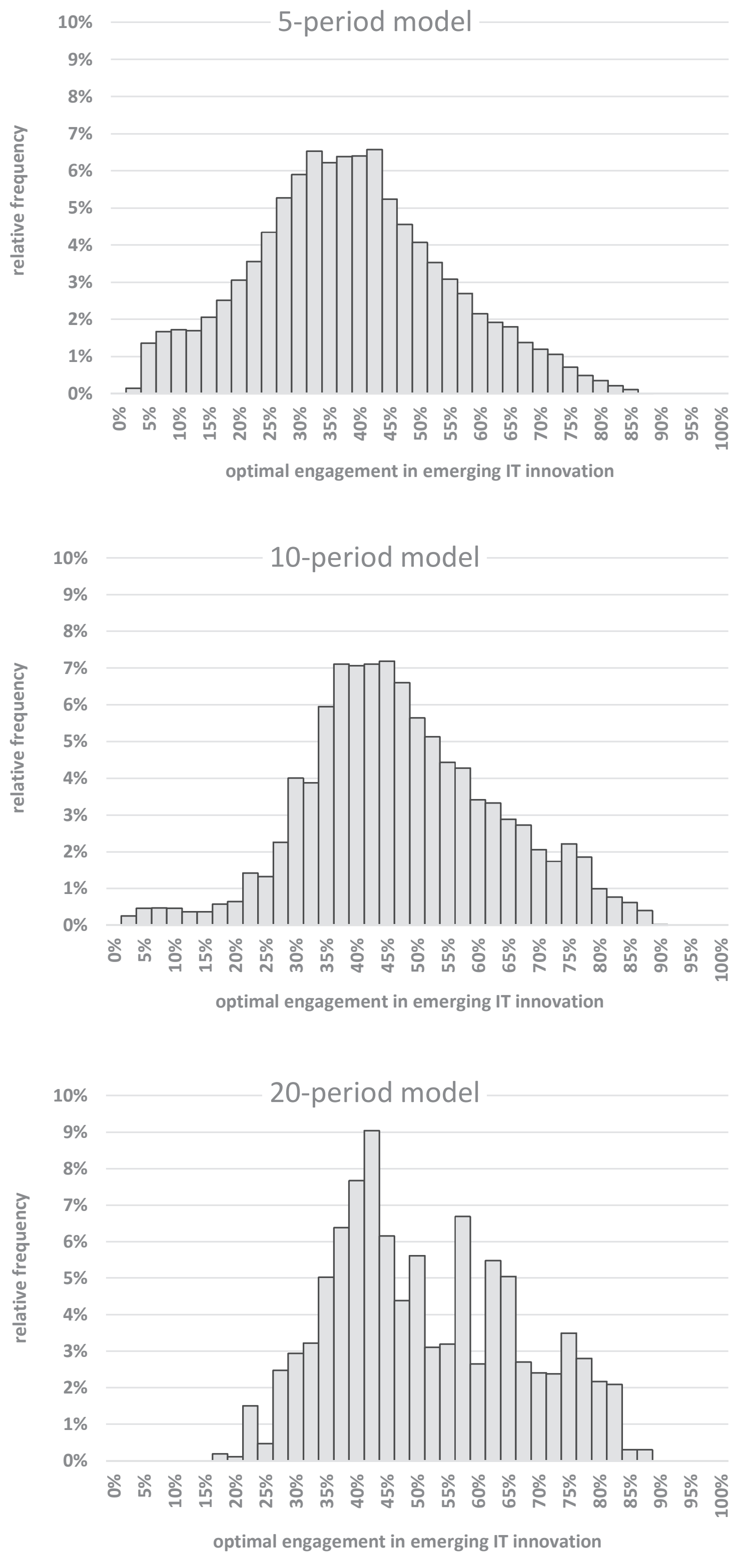

Figure 6. Histogram for $a_{\mathrm{t}}^{E^*}$ for 5-period, 10-period, and 20-period models

Using the histograms (see Figure 6), we can illustrate how often the optimal engagement $a_t^{E^*}$ (considering all points in time) lies in a certain interval (e.g., 0 - 2.5%). The histogram for the

5-period model is approximately symmetrical, while the histogram for the 10-period model is clearly positively skewed, with only a few values in the 0 - 30% range, and a considerable share of values in the 60 - 100% range. This supports the result that a longer planning horizon implies a higher engagement in E. This result is supported by the histogram for the 20-period model as well: while there are no values less than 15%, the majority of the values are located in the upper half of the scale.

What is even more interesting in the simulation's results is the development of the optimal share that is allocated to E over time (see Figure 7). As a first insight, we observe that the average optimal allocation to E stays almost constant in the 5-period model, as there is simply not enough time to benefit from organizational learning. However, it increases slightly but measurably from 41.5% to 50.1% for the 10-period model, and from 42.8% to 52.5% for the 20-period model. While this increase in the optimal allocation is approximately linear over time for the 10-period model, we can observe a strong increase in the first 10 periods and a subsequent leveling off for the 20-period model. The leveling off at rather constant investment shares in the last periods can be explained by the saturation effect of the innovator profile. At first glance, the observed optimal allocation to E is not completely comparable to the findings of prior empirical studies (which report ranges around 15%). However, when we consider the fact that our model incorporates dynamic organizational learning and focuses on only two types of investment, the upward deviation is reasonable in relation to what was reported in prior research, which distinguishes more types of innovations and does not incorporate organizational learning.

Further, the variation in the optimal engagement over time increases substantially for all three models. Apart from the variance (which increases slightly), this finding becomes even more obvious when looking at the 10/90%-quantiles and the minimum/maximum of the optimal engagement (see Figure 7).

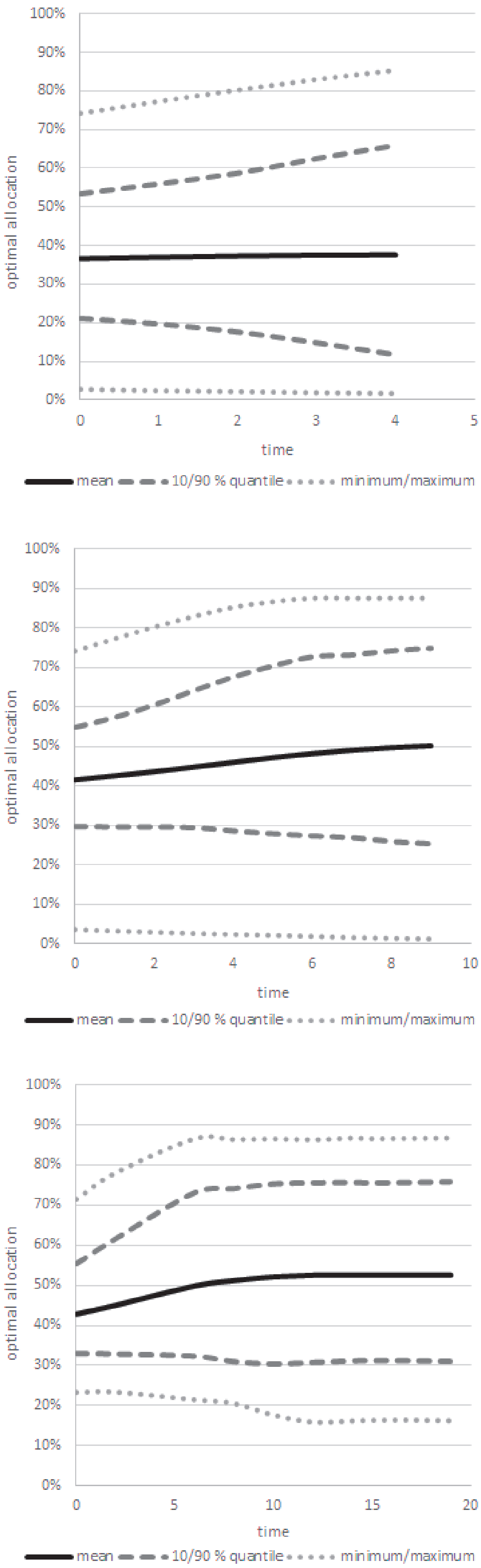

Figure 7. Results for $a_t^{E^*}$ over time after Monte Carlo simulation for 5-period, 10-period, and 20-period models

The general increase in optimal investment in E results from the fact that a company can increasingly benefit from investments in emerging IT innovations over the course of time because of the organizational learning effect. The rising spread is caused by the probabilities of success, the technology-specific impact factors of the investments, and the dynamic organizational learning. If a company has the opportunity to invest in promising innovations (with a high probability of success or a high technology-specific impact factor), and it benefits from the organizational learning effect, its investment in emerging IT innovations would increase substantially, as these would become even more attractive over time because of the increasing innovator profile. These circumstances cause the rising upward spread. If the innovation is not likely to generate high cash flows in the future (with low probabilities of success or technology-specific impact factors), the organizational learning effect would keep the engagement at a high level (in the beginning), as this affects all future periods and, therefore, increases all future cash flows resulting from E. However, the share would decrease or stagnate over time because of the investment's unprofitability and the finiteness of the planning horizon (as assumed in our simulation setting). These facts and the resulting extremely low engagement cause the rising downward spread.

Overall, our multivariate sensitivity analyses suggest that a company should dynamically adjust its engagement in E over time. This results from the fact that organizational learning positively affects the development of a company's innovator profile over time, thereby improving the company's ability to adopt emerging IT innovations successfully. In this context, we can also observe that the considered planning horizon has an appreciable impact on a company's investment behavior since the effects of organizational learning predominantly pay off in the long term.

II.2.4.5 Univariate Sensitivity Analyses

According to our multivariate sensitivity analyses for the three different planning horizons, the results from the 10-period model do not differ fundamentally from those of the 20-period model in terms of average engagement, dynamic adjustment of the optimal allocation, and the range for the optimal solution (at least for our parameter values). Only for the worst-case scenarios we can observe a considerable difference (as discussed in section 4.4); however, these parameterizations are no longer the focus of the univariate sensitivity analyses as we keep all the parameter values constant at the initial values from Table 3 (except the parameter under investigation). Thus, in the following discussion, we limit our analyses to the 10-period model and examine the development of the optimal allocation to E over time.

II.2.4.5.1. Influence of Success Probability ($\boldsymbol{p^E}$)

For the first univariate sensitivity analysis, we consider three different values for the success probability p^E. We analyze the model both *with* and *without learning effect (LE)*.

First, we find that according to our model and the parameterization, there is a positive relationship between the probability p^E and the optimal share a_t^E allocated to E in the model with learning effect as well as in the model without learning effect (see Figure 8). Further, we can conclude that under the given parameterization and considering the learning effect, companies should invest a substantial amount (~40%, ~49%, or 56%, depending on p^E) of their IT innovation budget in emerging IT innovations at $t = 0$, even though their probability to be institutionalized is not higher than 10%, 15%, and 20%, respectively. This is contrary to the findings of Kauffman & Li (2005), who (in a similar context) suggest adopting a new technology only if its probability to win is higher than 60%. The optimal engagement even increases over time (up to ~59%, ~72%, and ~79% in later periods) in order to take advantage of the beneficial effect of organizational learning. For all p^E, we observe a saturation effect regarding the innovator profile at $t = 7$, meaning that the company no longer adjusts its investment strategy because the innovator profile has reached its upper limit.

When comparing the results of the model *with learning effect* and those of the model *without learning effect* (even at $t = 0$), we see a considerably higher level of $a_t^{E^*}$ in the former model for all three values of p^E (see Figure 8). This leads us to assume that in this case, it is advantageous to increase the engagement in E in order to generate an organizational learning effect, and thus, to benefit at later points in time in the planning horizon.

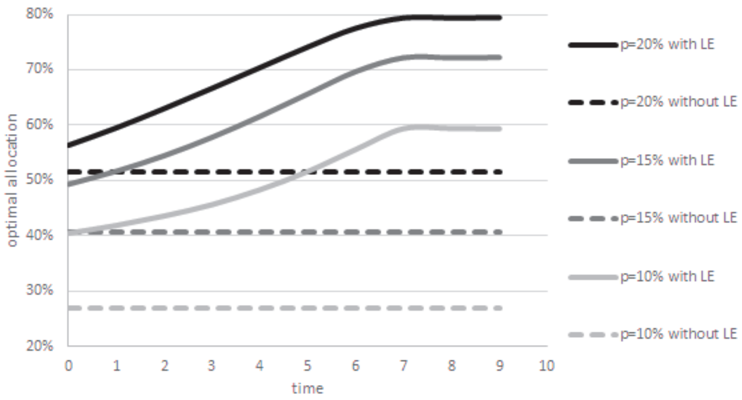

Figure 8. Optimal allocation of $ITIB$ to E with learning effect (LE) and without learning effect (LE) relative to p^E

In summary, the results support the major influence of uncertainty on the optimal IT innovation budget allocation, which in turn supports the prior findings reported by Kauffman & Li (2005), who claim that success probability is the most crucial factor. With increasing probability of success of an emerging technology, the company's optimal investment strategy changes to a substantially higher engagement in emerging IT innovations. Further, the consideration of organizational learning results in an increase in optimal investment shares over time. This can be explained by the fact that the company has already achieved a high level of organizational learning because of past investments, and now, it can benefit from its increased ability to innovate with IT. Because of the engagement in $E,$ companies perform better in the long run, which supports Wang's (2010) findings.

II.2.4.5.2. Influence of the Company's Individual Innovator Profile ($\boldsymbol{v_0^E}$)

Regarding the influence of the company's initial individual innovator profile v_0^E, we can draw analogies to the findings from section 4.5.1, which indicate that companies should invest in E depending on their level of innovativeness.

The *model without learning effect* shows that companies with a low initial innovator profile should invest only a low amount in E and allocate a higher share to M instead, as the latter type of innovation has a higher success probability and is better understood because there are more best practices available (see Figure 9). In the case of an increasing v_0^E, the optimal engagement in E increases up to a substantial level of about 40%. This supports the general assumption that the engagement in E requires a high ability to innovate with IT in order to avoid decisions that are based on gut feeling (Swanson & Ramiller 2004).

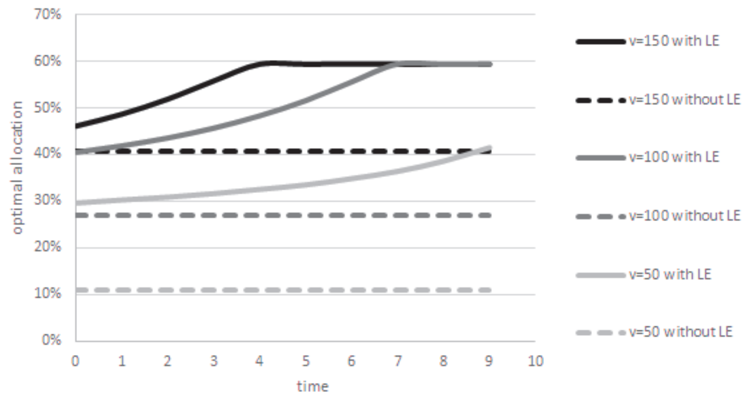

Figure 9. Optimal allocation of $ITIB$ to E with learning effect and without learning effect relative to v_0^E

The *model with learning effect* shows some interesting results, which differ from the results presented in section 4.5.1. In contrast to the analysis regarding the influence of the probability of success on the optimal engagement, the point in time where the saturation effect and the subsequent leveling off occur varies for different v_0^E. This is reasonable, as companies with an already high initial innovator profile only need to accumulate some knowledge through organizational learning until they reach the maximal level of the innovator profile assumed in our model, whereas an average innovative company or a below-average innovative company would require more time to reach maximal innovativeness. Moreover, in contrast to the analysis in section 4.5.1, the level of optimal engagement after reaching the maximal innovator profile (if this can be reached within the limited planning horizon) is the same for companies with different initial innovativeness. Thus, by adopting a dynamic and offensive investment strategy, even an average innovative company or a below-average innovative company can compete with an initially above-average innovative company in the long run.

Based on these results, we can hypothesize that companies are better off investing substantially in E, even if their innovativeness is below the average value of $v_t^{E^*} = 100$. Through substantial and continuous engagement in E, companies can increase the future profits resulting from investments in emerging IT innovations. This supports prior findings that “given sufficient time and resources, it is likely that a firm can develop the capability to innovate with IT” (Stratopoulos & Lim 2010) and become a leader in terms of innovativeness. In case of above-average innovativeness, companies can still increase their innovator profile by engaging in emerging IT innovations. However, these companies are likely to reach a saturation level regarding their ability to innovate with emerging IT at an earlier point in time, which would prevent them from outperforming the market and the average IT innovator completely.

II.2.4.5.3. Influence of the Market's Average Engagement in Emerging IT Innovations ($\boldsymbol{\alpha^E}$)

The extent of organizational learning (as modeled in this study) depends on a company's engagement in E compared to the market average. Therefore, the IT innovation budget that is allocated to mature and emerging IT innovations depends on the organizational learning effect (LE) gained by previous over- or under-investments relative to the average market engagement. Regarding a *model without learning effect,* this aspect is irrelevant, as the allocation is independent of the market's average engagement; thus, it is constant over time (see Figure 10).

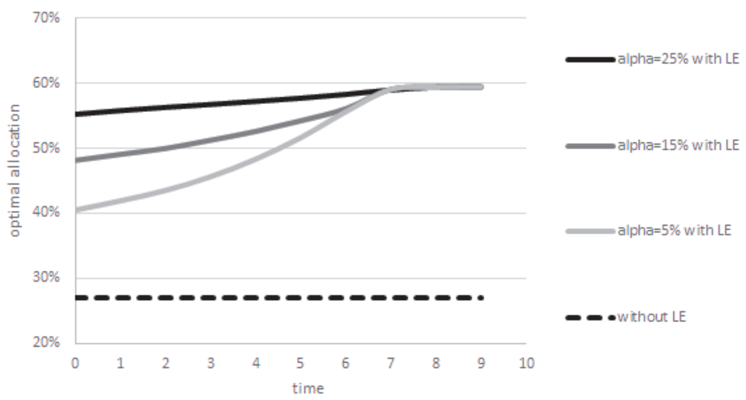

Figure 10. Optimal allocation of $ITIB$ to E and M relative to α^E

Regarding our *model with learning effect*, we find that a company's optimal investment strategy (for our parameterization) requires overinvestments compared to the market average because the company has to out-innovate the market through substantial engagement in E in order to be able to compete with or out-perform the market. This finding corroborates the empirical findings reported by Stratopoulos & Lim (2010) and Wang (2010), who find that a substantial engagement in E (above the market average) is required to compete with or outperform the market. Nevertheless, the optimal engagement $a_t^{E^*}$ depends on the market's average engagement α^E. In the earlier periods of the planning horizon, there is quite a difference in the optimal investment strategy (e.g., ~40%, ~48%, and ~55% for $t = 0$ with $\alpha^E = 5\%$, $\alpha^E = 15\%$, and $\alpha^E = 25\%$ respectively). Surprisingly, the strategies assimilate over time (~59% for $t = 7, 8, 9$). This is because of the saturation effect (discussed earlier) and the impossibility of increasing the innovator profile further through organizational learning. Thus, once maximal innovativeness is reached, the market's average engagement no longer affects the company's optimal engagement in E.

In summary, we hypothesize that companies always have to be aware of the average market engagement in E in order to develop an optimal strategy related to investments in emerging IT innovations. If the market is not very engaged in IT innovations, it would be easier to achieve experience-based competitive advantages and substantially outperform the average competitor or even become a systematic innovator. However, if the market has already been reasonably engaged in emerging IT innovations, the company's engagement in emerging IT innovations ought to be extremely high in order to race for market leadership. This finding matches the prior findings reported by Stratopoulos & Lim (2010), who find that it is much more difficult to remain a systematic innovator over time because of the need for persistent engagement in risky IT innovations. These results obtained from various scenarios that can be interpreted as dynamic environments (with high values for α^E) or stable environments (with low values for α^E) further support the findings reported by Lu & Ramamurthy (2010), who state that companies are better off matching their engagement in IT innovations to their competitive environment.

II.2.5 Implications

Decisions as to whether, when, and to what extent a company should invest in emerging IT innovations (which have the chance of becoming the next big thing as well as the risk of becoming a failing technology), often do not follow a well-founded analysis but are based on gut feeling. Regarding IT innovations that are in a hyped phase (i.e., emerging IT innovations), companies often jump on the bandwagon when it comes to investment decisions, although a large number of emerging IT innovations does not meet the high expectations. In this context, organizational learning plays an important role in improving the company's individual innovator profile and, thus, its ability to innovate with emerging IT regarding the core phases of an IT innovation process: *comprehension*, *adoption*, *implementation*, and *assimilation*. The continuous engagement in emerging IT innovations enables steady learning and makes companies capable of learning more about an emerging IT innovation, so that they can assess the innovation's development, situate the IT innovation in the company's specific context, and integrate it into the company's daily business. Thus, learning from the past engagement in emerging IT enables companies to innovate more economically in later periods.

To provide insights about the important causal relationships among the crucial factors, a well-founded analysis of the issues related to IT innovation (e.g., probability of institutionalization, market impact, intensity of competition) as well as company characteristics (e.g., ability to innovate properly, organizational learning) is required to depict the complexity of IT innovations more appropriately. Considering these aspects, we approach one of IT innovation theory's central research questions, namely, *whether, when, and to what extent* a company should innovate with information technology (Swanson & Ramiller 2004), using a dynamic n-period optimization approach that optimizes the allocation of a periodical IT innovation budget to different types of IT innovations by incorporating organizational learning.

Our analyses theoretically showed that there is an optimal investment strategy in mature and emerging IT innovations, and that this strategy complies with the constraints of our decision framework. Thus, our approach incorporates both a portfolio perspective considering mature and emerging IT innovations and a dynamic perspective, as we determine the optimal allocation of an IT innovation budget at different points in time by considering different possible scenarios. Moreover, our approach covers both the specifics of mature and emerging IT innovations (such as their uncertainty and their technology-specific impact factor) and company-specific characteristics, such as the individual innovator profile. Additionally, it incorporates the dynamic development over time because of the learning aspects as well as the market's average engagement. Depending on the level of these parameters and their interrelationship, the allocation of the IT innovation budget to emerging IT innovations should be either increased or decreased. Thus, our approach allows us to derive the following implications for research and practice, thereby addressing the research questions and contributing to the extant literature:

- A company's IT department is well advised to always allocate at least a small portion of its budget to emerging IT innovations regardless of the company's individual innovator profile, probability of success, or the overall market's engagement. [*whether*]

- Even a company that is initially well below average in terms of innovativeness should invest in IT innovations fundamentally to gain experience-based competitive advantage and to catch up with the market or even the market leaders. [*whether*]
- With an increasing planning horizon of the IT innovation investment strategy, the optimal engagement increases, as the company can benefit from organizational learning in later periods. [*whether*]
- Because of organizational learning, which is particularly beneficial in a long-term planning horizon, companies should substantially invest in emerging IT innovations, even if their probability of success has not reached a high threshold. [*when*]
- As a company's ability to innovate changes over time because of organizational learning, the optimal engagement in IT innovation investments needs to be adjusted dynamically over time in order to maximize profit. [*when*]
- If a company reaches the maximal innovativeness, the optimal engagement in IT innovations levels off at a constant share, as no further improvement (compared to the market) is possible. [*to what extent*]
- Considering organizational learning in IT innovation investment decisions implies a higher engagement compared to not considering organizational learning. This can be explained by the fact that the possibility to outperform the market through continuous learning enables a company to gain long-term competitive advantages. [*to what extent*]

II.2.6 Theoretical and Practical Limitations and Outlook

We proposed an analytical model that delivers reasonable initial results by identifying and analyzing the relevant causal relationships in IT innovation investment decisions. Nevertheless, the analytical model and our findings might not be suitable for practical application without some company-specific adjustments. Following Kauffman & Li (2005), our model aims at "an analogy between the technical details of the decision model and the exigencies of its application in an appropriate managerial context." Some of the aspects that are not covered by this study or that require further methodological effort in order to be transferable directly into practice are listed here. This study focused on the optimal allocation of a given budget taking organizational learning into consideration. Further steps of the complex decision-making process related to investments in IT innovations as well as external factors were not considered; therefore, further research is required to address these aspects. In practice, companies usually should consider each IT innovation individually and then mindfully decide whether it is appropriate to invest in that innovation, and how the innovation could be managed to achieve the best results. Thus, determining the extent of the engagement by considering organizational learning is only one part of the IT innovation investment process. Further, we did not evaluate whether all the companies that want to invest in IT innovations could adopt the optimization model developed in this study. There would be differences between multi-billion-dollar companies like Google or Apple and smaller companies or start-ups. Further, we did not model an endogenous market; therefore, we did not consider the interdependencies between the dynamic investment strategies of competitors. Considering the investment behavior of the market participants and the implementation of competition with regard to emerging IT innovations would most likely influence the decision-making process. As the implementation of such effects would go beyond the scope of this study, this highly interesting investigation is left for further research. Moreover, currently, we cannot determine whether this approach is applicable to all sectors, such as computer chips manufacturers, app developers, and social media start-ups. Further research could explore whether the proposed approach is suitable across sectors. Nevertheless, the causal relationships identified in this study should allow for the derivation of general propositions related to IT innovation investments.

An empirical testing of the model’s results and its parameters using real-world data should be taken up in future research. To incorporate the optimization model (including its parameterization) into real-world decision-making processes, approximate values for the model’s parameters need to be estimated. This could be done via educated assessments using experts or consultants based on experience from previous investments, or through benchmark analyses within the market. While some factors are rather company-specific and need to be estimated by each company, others are technology- or market-specific and do not differ across companies.

It has to be noted that the model’s inherent interpretation of the IT innovation’s value is rather abstract. This means that our model is limited to quantifiable and attributable components of value. When applying our model, factors that are hard to quantify (e.g., technological acceptance by users) would have to be either neglected or converted into quantitative figures through appropriate methods. Additionally, we have not considered minimum or maximum investments in our analysis. However, it might be the case that a technology requires a minimum engagement in order to be applicable reasonably. Therefore, the inclusion of a minimum or maximum value that may or may not be overstepped should be part of an extension of this study. Moreover, our model assumes a constant market, as the average innovator profile does not change over time. In order to address dynamic market adjustments such as herd behavior or a "rush" in an emerging IT innovation, future research should explore the possibility of allowing for a dynamic average engagement in IT innovation and, therefore, a dynamic average innovator profile. Further, our model reasonably assumes a risk-neutral decision maker. The extension of the model in a more general manner and the incorporation of a risk-averse decision maker (who considers risk interdependencies between the different IT innovation investments) should be considered in future research. The differentiation between certain specific mature and emerging IT innovations and the consideration of different success probabilities could also be taken up. Finally, although modeling organizational learning via a learning-by-doing approach is suitable for obtaining first results and indicators, the modeling of learning from communities and the so-called fashion-setting networks might provide even deeper insights.

Although the proposed model pictures reality in a slightly constrained way, it provides the basis for companies to plan and improve their IT innovation strategy related to emerging technologies. Moreover, it is a theoretically sound economic approach, which allows for further development and provides insights about IT innovation-related issues. Therefore, this study serves as the basis for further analytical research on emerging IT innovations and contributes to the understanding and improvement of this research stream.

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II.3 Research Paper 3: "Evaluating Different IT Innovation Investment Strategies from an *Ex Ante* and *Ex Post* Evaluation Perspective."

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Published in:	International Journal of Innovation and Technology Management, 13(4), 2016

Abstract:

Contrary to mature IT innovations, fashionable IT innovations are hyped but lack institutionalization. Since an appropriate evaluation of these innovations is rather complex, companies often choose fixed investment strategies that neglect effects of organizational learning through continuous innovating. Hence, we develop a dynamic optimization model that determines the optimal budget allocation to mature and fashionable IT innovations by considering organizational learning. Furthermore, we evaluate various investment strategies both from an ex ante and an ex post perspective. Thereby, we focus on a company's

innovativeness and draw conclusions about the superiority of different investment strategies regarding expected NPV and its volatility.

II.3.1 Introduction

The high uncertainty about an IT innovation's development makes it difficult to estimate whether a technology will be the “next big thing" that guarantees long-term success or whether it just remains a short-term hype that even might fade away, as it was the case for technologies like WAP or virtual worlds. Contrary to mature IT innovations where the future development can be estimated comparatively easily, literature defines IT innovations which are undergoing a hyped phase as fashionable IT innovations (Wang 2010; Baskerville and Myers 2009; Fichman 2004). Often enough, such new emerging technologies due to their novelty and immaturity often “[…] impose significant knowledge barriers that early adopters have to overcome […]" (Ravichandran and Liu 2011). To overcome such barriers, literature especially emphasizes the importance of a steady engagement in new emerging technologies to improve the process of organizational learning (Fichman and Kemerer 1997), and thus a company's ability to implement innovations successfully. By that, the company's ability to innovate (also referred to as a company's innovativeness or a company's innovator profile) and its development due to organizational learning in the long run heavily impact the company's success regarding an engagement in fashionable IT innovations (Häckel et al. 2013b), Häckel et al. 2017). Therefore, these factors should be considered adequately when evaluating the engagement in fashionable IT innovations.

To allow for a well-founded allocation of a company's IT innovation budget, appropriate methods which consider the development of a company's innovator profile are necessary to determine an optimal IT innovation investment strategy regarding fashionable as well as mature IT innovations. However, management's uncertainty, missing data, or political reasons in practice often do not allow for such a well-founded evaluation and thus lead to rather simple, fixed IT innovation investment strategies which can be compared to naive diversification rules in financial portfolio management. Those fixed IT innovation strategies are easy to plan, implement and control but do not adjust to new developments regarding the company's ability to innovate over time (Nagji and Tuff 2012; Swanson and Ramiller 2004; Häckel et al. 2013b). As a result, such fixed strategies might deviate from a theoretically optimal solution which is based on a well-founded evaluation method considering dynamic adjustments of the innovator profile over time by means of an organizational learning process. Hence, compared to the theoretical optimum fixed IT innovation strategies might lead to an economic damage (e.g. lower value contribution through a nonoptimal allocation of the IT innovation budget). Against this background, it is of major interest for companies whether an IT innovation strategy that adjusts over time is beneficial compared to a fixed IT innovation strategy and how substantial the difference is. As a company's optimal IT innovation strategy essentially depends on its ability to innovate (Häckel et al. 2013b; Häckel et al. 2017; Stratopoulos and Lim 2010), we thereby in particular examine the advantageousness of an optimal dynamic investment strategy for companies with different innovativeness.

For that, we first take an *ex ante* perspective and develop a dynamic n-periods optimization model which theoretically determines the optimal *ex ante* allocation of an IT innovation budget to fashionable and mature IT innovations. Thereby our model builds on central findings of IT innovation theory as well as aspects of organizational learning. By analyzing the optimization model we aim to answer our first research question which focuses on a company's ability to innovate and its influence on the success of a certain IT innovation investment strategy:

- ***Research Question 1.*** *From an ex ante perspective: Regarding the expected NPVs, to what extent do the optimal IT innovation investment strategies of companies with different abilities to innovate differ from each other?*

Building on the analysis of theoretically optimal IT innovation investment strategies, we in a next step aim to analyze to what extent such optimal strategies outperform fixed IT innovation investment strategies. By means of this analysis, we are able to address our second research question:

- ***Research Question 2.*** *From an ex ante perspective: How substantial is the expected economic advantage of a theoretically optimal dynamic IT innovation investment strategy compared to a fixed IT innovation investment strategy and how is this economic advantage influenced by a company's ability to innovate?*

Though a certain strategy might be beneficial from an *ex ante* perspective, taking an *ex post* perspective allows us to gain valuable insights regarding the question of how an *ex ante* determined IT innovation strategy performs in different realized scenarios. For management practice, such an *ex post* perspective is crucial to allow for a continuous monitoring, an on-going re-evaluation and a possible readjustment of a certain IT innovation investment strategy due to changes in internal or external influencing factors. A careful *ex post* evaluation of IT innovation strategies might also provide valuable insights for improving future *ex ante* investment decisions and therefore contributes to continuous organizational learning. Furthermore, the *ex post* evaluation of investment strategies usually builds the basis for future budget allocations to IT and business divisions and variable remuneration of managers. Thus, next to deriving optimal *ex ante* decisions we adopt an *ex post* perspective and examine whether a certain IT innovation strategy might have been superior compared to the chosen one from an *ex post* point of view. By examining different (extreme) scenarios in an *ex post* backtesting approach, we enrich previous literature which often exclusively focused on an *ex ante* evaluation of IT innovation investments (Fridgen and Moser 2013; Häckel et al. 2013a; Häckel et al. 2013b; Häckel et al. 2017). Thereby, we in particular aim at analyzing if a designated *ex ante* optimal investment strategy also outperforms a fixed investment strategy from an *ex post* perspective. In doing so, we mainly focus on the volatility of an *ex ante* optimal IT innovation investment strategy, i.e. how the economic success of this investment strategy varies across different scenarios (e.g. whether the IT innovation became institutionalized or turned out to be a failing technology). This offers helpful insights about the stability of certain IT innovation investment strategies across different scenarios, an aspect that is highly relevant for management practice due to the extremely uncertain development of IT innovation investments.

Since the *ex ante* optimal IT innovation budget allocation strongly depends on a company's ability to innovate, we also analyze from an *ex post* perspective how the results are influenced by a company's innovator profile. This raises our third research question:

- ***Research Question 3.*** *From an ex post perspective: How does a company's ability to innovate influence the volatility of an optimal IT innovation investment strategy's economic success across different realized scenarios?*

Analogously to the *ex ante* perspective, based on the comparison of different optimal IT innovation investment strategies, we in a next step aim at comparing the optimal dynamic investment strategy with a fixed and therefore constant investment strategy:

- ***Research Question 4.*** *From an ex post perspective: How do different scenarios and a company's ability to innovate affect the advantageousness of an ex ante determined optimal and therefore dynamical IT innovation investment strategy compared to a fixed IT innovation investment strategy?*

Our approach is closely related to the basic idea of the research cycle of Meredith et al. (1989), as our mathematical approach provides the basis for generating hypotheses for future tests within empirical research. Thereby, we focus on analyzing different investment strategies from an *ex post* perspective, in order to evaluate the investment strategies for concrete realizations.

The paper is organized as follows. First, we describe the idiosyncrasies of an engagement in fashionable IT innovations in more detail and give an overview of the relevant IT innovation, and IT fashion literature. After that, we develop and analyze our model to answer the stated research questions and derive first results and propositions. This serves as the basis for a discussion of the contributions to research and practice, possible limitations and the potential starting points for future research.

II.3.2 Definitions, Problem Context and Related Work

To lay the theoretical foundation for our model of determining the optimal engagement in fashionable and mature IT innovations, we define two different kinds of IT innovations and provide an overview on previous IT innovation and IT fashion research as well as selected aspects regarding organizational learning theory. IT innovation literature traditionally focused on a company's innovator profile, i.e. ist ability to innovate easy, effective, and economic due to a set of variables like company size, structure, knowledge, or compatibility (Grover et al. 1997). However, several authors claim to consider other IT innovation related issues (e.g. probability of institutionalization, learning by doing, intensity of the market's innovativeness) in the selection and evaluation of IT innovations (Fichman 2004; Häckel et al. 2013a; Swanson and Ramiller 2004). Incorporating an IT innovation's outcome in its lifecycle is closely linked to the concept of technology adoption cycles (Rogers 2003) and Gartner's "Hype Cycles" (Fenn and Raskino 2008). Latter categorizes an IT innovation's lifecycle in a technology trigger, a peak of inflated expectations, a trough of disillusionment, a slope of enlightenment, and a plateau of productivity. Especially the first three milestones mark the phase when an IT innovation has fashionable aspects, but an unclear destiny (Häckel et al. 2013a).

Therefore, the IT innovation types are differentiated according to their current diffusion and maturity (Tsui et al. 2009; Wang 2009).

Fashionable IT innovations: IT innovations in an evolutionary phase between technology trigger and trough of disillusionment and thereby fashionable (Fenn and Raskino 2008); Wang

2010). An engagement promises competitive first mover advantages in case of wide adoption and institutionalization. However, estimations about their future evolution are diffcult as the hype might fade away without reaching a long-term productivity. Currently, technologies like 3D printing, social analytics, or near-field-communication (NFC) are fashionable (Wang 2010; Gartner 2012).

Mature IT innovations: IT innovations that already reached an evolution between slope of enlightenment and plateau of productivity (Fenn and Raskino 2008) or are adopted by a significant amount of the market but lack mass adoption. Due to their maturity and thus roughly certain future evolution, no early mover advantage can be realized anymore. Current examples for mature IT innovations are customer relationship management (CRM) or enterprise resource planning (ERP) (Wang 2010).

In this vein, IT fashion theory extends the traditional IT innovation focus and argues that the massive adoption of certain (IT) innovations not only is to explain through the possibility to improve productivity but also through its propagation through a fashion-setting-network (Wang 2010; Abrahamson 1991). Previous literature like Dos Santos and Peffers (1995) or Hoppe (2000) in this context examined the advantageousness of first or late mover strategies regarding new emerging technologies. Others like Lu and Ramamurthy (2010) or Wang (2010) showed general support for the assumption that proactive IT innovation leaders that engage in IT innovations in a fashionable phase can outperform their competitors. Though all this research provides valuable insights regarding investments in fashionable IT innovations, it is rather generic without explicitly examining how the idiosyncrasies of fashionable IT innovations might affect an optimal engagement. In particular, the consideration of a fashionable IT innovation's risk of getting stranded plays a central role, as in this case those investments cannot produce the required benefits or even any benefits to recover their implementation costs (Fichman 2004). As one of the few, Kauffman and Li [2005] address this challenge arguing that technology adopters are better off by deferring investments until the technology's probability to become widely accepted reaches a critical threshold. The approach of Häckel et al. (2013a) examines the valuation error that occurs from applying fixed strategies regarding the investment in fashionable IT innovations. However, their approach is limited to a two-period-dynamic optimization model without considering organizational learning. Furthermore, Häckel et al. (2013b) and Häckel et al. (2017) examine IT innovation investment strategies considering organizational learning, but solely focus on *ex ante* perspective and neglect an *ex post* perspective. For that reason, they are not able to evaluate the *ex ante* determined strategy from an *ex post* perspective. Consequently, this study considerably extends the work of Häckel et al. (2013b) and Häckel et al. (2016) by means of a backtesting approach.

Looking at fashionable IT innovations which by nature are characterized by high immaturity and a lack of thorough understanding or best practices, a well-founded IT innovation process which includes the phases comprehension, adoption, implementation and assimilation (Swanson and Ramiller 2004), is a challenging task. Though the engagement in mature IT innovations also requires experience from organizational learning, a lack of experience in these four phases can largely be compensated by existing best practices or experiences of other companies. Thus, this paper's organizational learning analysis focuses on the ability to innovate with fashionable IT (for example through carrying out successful or unsuccessful projects (Caron et al. 1994). Various literature sources have found that organizational learning affects a company's individual innovator profile and thus improves its ability to comprehend, adopt, implement, and assimilate IT innovations successfully (Fichman and Kemerer 1997; Ashworth et al. 2004; Wang and Ramiller 2009). As learning through engagement in IT innovations improves a company's overall performance from innovating with IT (Tippins and Sohi 2003), the examination of how organizational learning affects the theoretically optimal engagement in fashionable IT innovations is highly important. Previous research empirically or qualitatively emphasized that learning aspects in an IT innovation engagement, learning through experiments, and persistence are important for improving the ability to innovate with IT (Lucas et al. 2007; Stratopoulos and Lim 2010; Wang and Ramiller 2009; Swanson and Ramiller 2004). To measure the outcome of organizational learning, previous literature applied learning curves which describe the development of a company's ability to innovate (Ashworth et al. 2004; Robey et al. 2000; Epple et al. 1991).

Regarding the effect of organizational learning on a company's innovator profile and thus on the engagement in fashionable IT investments, Stratopoulos and Lim (2010) empirically demonstrate that for becoming a systematic innovator who outperforms competitors, persistence and learning regarding the engagement in new emerging IT innovation is inevitable. Due to continuous learning, systematic innovators have more experience in selecting and implementing IT which is still in a fashionable phase but eventually appropriate for the company, as well as in evaluating new applications in the company's context (Swanson and Ramiller 2004). Thus, IT fashion investments not only depend on the acceptance of the technology by a broad range of companies but also on the effect of organizational learning through a continuous engagement which improves the company's ability to innovate with new IT. This ability also can be described as the company's individual innovator profile (Fichman 2004). Barua et al. (1995) found that those companies which are more effcient in utilizing investments in IT are more likely to be aggressive regarding IT investments and thus probably also with regard to their engagement in fashionable IT innovations. Thus, innovating with new emerging IT requires continuous learning to bridge the gap between existing knowledge, experience, as well as abilities and those aspects that a new emerging IT innovation requires companies to know (Fichman and Kemerer 1997; Weiling and Kwok Kee 2006).

Despite this rich empirical and qualitative literature regarding organizational learning in the context of IT innovation investments, formal-deductive and mathematical models are virtually absent in this field. Thus, this paper aims at contributing to this research gap by transferring findings from previous literature to a formal-deductive mathematical model which incorporates the effect of organizational learning on a company's individual innovator profile and thus the optimal engagement in fashionable IT innovations. By doing that, the model aims at providing hypotheses that can be tested empirically afterwards.

II.3.3 Toward an Optimal IT innovation Investment Strategy Considering Fashionable Technologies and Organizational Learning

In accordance with the design-science research guidelines by Hevner et al. (2004) as well as Gregor and Hevner (2013) we in the following develop a dynamic optimization model for determining the optimal allocation of a periodical IT innovation budget to mature and fashionable IT innovations. We then evaluate the model's results by using a backtesting approach in order to derive propositions for the most suitable IT innovation investment strategy regarding fashionable IT innovations.

Our analysis' focus is on the IT innovation portfolio of a company whose strategic IT innovation investments are regularly re-allocated. In every point in time t, the company decides how to allocate a periodical IT innovation budget to two different types of IT innovations (*mature* vs. *fashionable*) to maximize its expected cash flows over the planning horizon.

As both types of IT innovations bear severe risks as well as tremendous opportunities, companies are well advised by incorporating future developments into their IT innovation strategy. To avoid gut feeling investments, methodically rigor models are needed, although they might have to be adjusted to suit the requirements of real-world investment problem settings. Due to that reason, Hevner et al. (2004) argue that the overemphasis on rigor can lessen relevance and that both paradigms, rigor and relevance, are relevant for all IS related research. Therefore, in the following section our modelling assumptions are presented in order to build up the theoretical IT innovation investment strategy evaluation model step-by-step without distorting the real-world investment problem.

II.3.3.1 Fundamental assumptions, the model and the objective function

Assumption 1: A company's IT department (in the following we do not differentiate between the IT department of a company and the company itself) invests a periodical, constant IT innovation budget $ITIB$ at points in time $t = 0, 1, \dots, n$, each for one period. We define $a_t^F \epsilon [0,1]$ as the share of $ITIB$ that is invested in fashionable IT innovations *(F)* at t. Since companies naturally do not spend their whole IT innovation investment budget on fashionable IT innovations (Lu and Ramamurthy 2010; Hoppe 2000), we define $a_t^M = 1 - a_t^F > 0$ as the share of $ITIB$ that is invested in mature IT innovations *(M)*.

The allocation of the $ITIB$ to different types of IT innovations thereby follows Ravichandran and Liu (2011), who state that a company's IT investment strategy refers to its "[…] strategic orientation toward IT investing in terms of scale and proactiveness". Thus, we model the scale in terms of the share allocated to fashionable and mature IT innovations, respectively. Additionally, we also include proactiveness in terms of a company's "[…] attitude toward technology adoption […]" (Ravichandran and Liu 2011) by differentiating between IT innovations with different maturities and potential risks. Figure 1 shows the split of $ITIB$ into the two investment alternatives F and M.

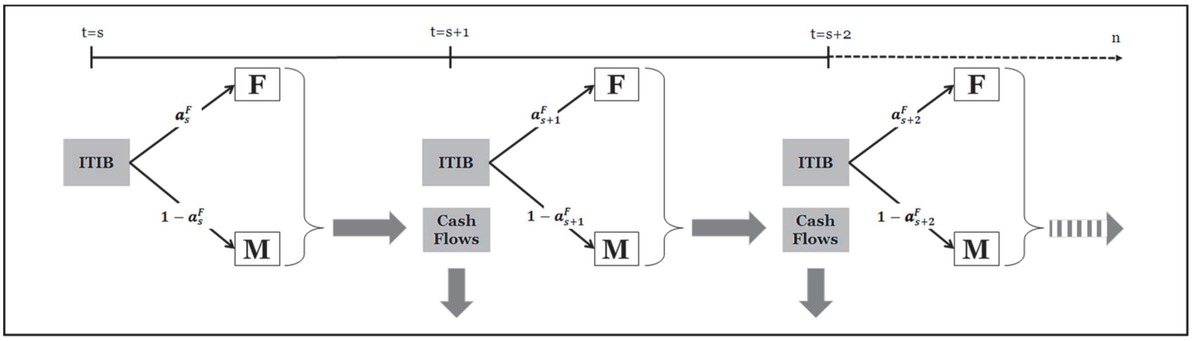

Fig. 1. The investment setting at $t = s, s+1$ and $s+2$

Assumption 2: The IT innovation portfolio's cash flows CF_t^{PF} consist of the investment's cash flows CF_t^F and CF_t^M resulting from the fashionable IT innovation and the mature IT innovation investment:

$$CF_t^{PF} = CF_t^F + CF_t^M \text{ with } t \in \{1,2,\dots,n\} \tag{1}$$

The investment alternatives *F* and *M* generate specific cash flows, depending on the fashionable IT innovation's destiny and the mature IT innovation's success in the market. To model the idiosyncrasies of the investment setting in more detail, we take a closer look at the realized cash flows.

Assumption 3: The cash flows CF_t^F and CF_t^M resulting from the investments in *F* and *M* follow a strictly monotonically increasing, concave function, which is differentiable twice and depends on the IT innovation budget's share a_{t-1}^i with $i \in [F, M]$ that was allocated to *F* and *M*, in the previous period:

$$CF_t^i(a_{t-1}^i) = \left(a_{t-1}^i \cdot ITIB\right)^{q_z^i} \cdot v_{t-1}^i \quad \text{with} \tag{2}$$

$$q_z^i \in [0,1), \quad v_{t-1}^i \in R^+, \quad i \in \{F, M\}, \quad z \in \{u, d\} \tag{3}$$

A monotonically increasing cash flow function is reasonable due to the fact that a higher investment makes a deeper understanding and a broader implementation of the technology possible and therefore provides more opportunities to create value out of the investment later on (Melville et al. 2004; Fichman 2004). Furthermore, an increasing investment in *F* or *M* is characterized by a diminishing marginal utility regarding $CF_t^i(a_{t-1}^i)$, i.e., $\partial^2(CF_t^i(a_{t-1}^i))/\partial^2 a_{t-1}^i < 0$, according to production theory (Stiglitz 1993). Hence, a first engagement in IT innovation creates more value than the additional increase of an already quite high investment as the initial engagement enables entering a market or becoming reasonably familiar with a technology (Stratopoulos and Lim 2010; Lu and Ramamurthy 2010). Moreover, due to the diminishing marginal utility, a very high investment in fashionable IT innovations is not unlimited beneficial, since at some point the cash flow falls below the invested budget which leads to a negative sum of $ITIB$ and the cash flows of the fashionable IT innovation even if the latter is institutionalized and accepted by the market.

The constant factor q_z^i with $i \epsilon \{F, M\}$ and $z \epsilon \{u, d\}$ can be interpreted as a technology-specific impact factor describing the impact degree of F and M, e.g., its acceptance by customers or employees or its easiness of integration into existing IT infrastructure which influences the investment's cash flow (Fichman 2004; Haner 2002). As fashionable IT innovations, in case they are institutionalized and accepted by the market, usually have a higher impact and therefore generate higher cash flows for the company (Lu and Ramamurthy 2010; Wang 2010), we assume F's technology factor q_z^F with $z \epsilon \{u, d\}$ to be generally higher than M's q_z^M with $z \epsilon \{u, d\}$, i.e., $q_z^F > q_z^M \; \forall \; t = 1, \dots, n$ with $z \epsilon \{u, d\}$. However, as an IT innovation's impact on the market is difficult to predict, both scenarios, a high impact ("upside" with $z = u$) and a low impact ("downside" with $z = d$), have to be considered (Fenn and Raskino 2008). Whereas upside scenarios for example can be interpreted as high acceptance by customers, a downside scenario can be characterized by difficulties within the integration in existing processes or even the case of getting stranded. Therefore, we model both, upside and downside scenario for F and M into the technology-specific impact factor, i.e., $q_u^i > q_d^i \; \forall \; t = 1, \dots, n$ with $i \epsilon \{F, M\}$, and by that incorporate uncertainty about the IT innovation's possible outcome. Thereby, cases with $q_d^F < q_u^M$, are possible. Though modeling only positive or negative scenarios simplifies real world scenarios, it incorporates the borderline cases which are of high relevance for this analysis.

The factor $v_t^i \epsilon R^+$ with $i \epsilon \{F, M\}$ can be interpreted as the company's individual innovator profile at t describing the company's ability to engage in an IT innovation economically, quickly and efficiently (Fichman 2004; Swanson and Ramiller 2004). For easier interpretation, we level a company that is average innovative (compared to the market) at t with $v_t^{i^*}$, below-average innovative with $v_t^i < v_t^{i^*}$, and above-average innovative with $v_t^i > v_t^{i^*}$ (Stratopoulos and Lim 2010). Thus, $v_t^i \epsilon R^+$ with $i \epsilon \{F, M\}$ depicts a company's innovativeness in comparison to the market average which suits the usually intense competition in dynamic and technology driven market environments (Lu and Ramamurthy 2010). As existing literature (Wang and Ramiller 2009; Stratopoulos and Lim 2010; Nagji and

Tuff 2012) puts emphasis on the fact that a steady engagement in *new emerging* IT is important for a company's innovativeness and for continuous learning as well as the fact that experiments are mostly the source of transformational innovation, our analysis focuses on the engagement in *fashionable* IT innovations. This is reasonable as, in contrast to mature IT innovations, fashionable IT innovations require a substantially higher level of experience due to a lack of best practices. Consequently, we can narrow our analysis down to the effect of organizational learning on the company's innovator profile regarding v_t^F. Hence, v_t^M is assumed to be constant over time.

Summarizing, q_z^i with $i \in \{F, M\}$, $z \in \{u, d\}$ as well as $v_{t-1}^i \in R^+$ with $i \in \{F, M\}$ consolidate a variety of different factors. Though these factors could be split up in several sub-dimensions, we focus on a more general level to keep the balance between rigorousness and interpretability.

Assumption 4: The development of a company's individual innovator profile regarding fashionable IT investments v_t^F follows a learning (by doing) curve in form of a *s*-curve which depends on the engagement a_{t-1}^F, the market's average engagement α^F, the maximal periodical growth rate β and the proportionality factor k:

$$v_t^F = v_{t-1}^F \cdot L_{t-1}(a_{t-1}^F) = \quad (4)$$

$$= v_{t-1}^F \cdot \left((1-\beta) + \frac{2 \cdot \beta}{1+exp\,(-k \cdot (a_{t-1}^F - \alpha^F))}\right) \quad (5)$$

Though learning curves are an accepted phenomenon in IT innovation literature (Ashworth et al. 2004; Robey et al. 2000), the fact that measuring organizational learning exactly is virtually impossible or at least very demanding has generated various different ways of modeling the increase in knowledge over time. In analogy to approaches where the required labor per produced united decreases with an increase in production (Epple et al. 1991), we model a learning by doing relation. This means that a company experiences organizational learning through the engagement in fashionable IT innovation. Regardless of whether the fashionable IT innovation later becomes institutionalized or not, the company improves its individual innovator profile as it might be able to better assess, select and implement another fashionable IT innovation. Of course, one cannot guarantee that every experience is always helpful for future technologies. However, we at this point find it appropriate to simplify from reality to limit complexity and due to the fact that up to a certain degree, all kind of experience is useful for a later engagement, implicitly assumes a full spillover effect. This also is supported by previous literature which emphasizes that companies require steady engagement in new emerging technologies to stay at the forefront of innovativeness (Wang and Ramiller 2009; Stratopoulos and Lim 2010; Nagji and Tuff 2012). For that, we model the development of a company's innovator profile regarding fashionable IT innovations via an s-curve (Kemerer 1992; Raccoon 1996) as this type is suitable to depict the increasing but limited ability to innovate with IT. As we measure v_t^F in comparison to the market average, the included shift assumes a competition-based learning which depends on the market's average engagement in fashionable IT innovations α^F. This means that v_t^F only increases if the company invests more in fashionable IT than the market's average does. Consequently, v_t^F decreases relative to the market in case its engagement is lower than the market average α^F. This is reasonable as a company might be innovative from its isolated view with a (subjectively) high engagement in new emerging technology but compared to a market which engages even more might be rather below-innovative. The growth rate β specifies the maximal periodical increase respectively decrease in the innovator profile generated by the learning effect. The proportionality factor k is an indicator how sharply the curve increases and therefore how strongly the difference between the company's investment level and the market average influences the learning effect. In addition, we restrict v_t^F to a global upper limit G, i.e., a level of saturation of innovativeness. As these three parameters β, k and G are not the focus of our model evaluation, we do not explicitly explain their influence on the optimization model and therefore the optimal engagement in emerging and mature IT innovations.

To sum up, our approach of modeling organizational learning inherits the assumption that engaging in fashionable IT innovations increases organizational learning. However, as our model aims at providing first propositions rather than a one-to-one application to real-world business problems, modeling the development of a company's innovator profile in this way is appropriate for the purpose of this paper.

Assumption 5: The IT innovation's lifecycle is broken down and modeled as a time frame including two periods whereas $t = s$ describes the point of time when a fashionable IT innovation emerges and $t = s + 1$ describes the point of time when its destiny turns out. Consequently, in case that a fashionable IT innovation becomes institutionalized, $t = s + 2$ describes its plateau of productivity's altitude. As fashionable and mature IT innovations recur constantly over time, we assume that the described time frame and the scenarios for the fashionable and mature IT investments repeat every two periods.

Breaking an IT innovation's lifecycle down into a recurring time frame including two periods simplifies the matter but allows us to analyze a longer time frame of subsequent decisions regarding the allocation to mature and fashionable IT innovations. Thus, we analyze an investment strategy over a longer time frame by focusing on two periods which are sufficient to schematically model the most crucial idiosyncrasies of the investment problem setting as in this phase an IT innovation is "in fashion" (Wang 2010).

Assumption 6: Uncertainty about the mature and fashionable IT innovation's possible outcome (i.e., which of the scenarios q_u^i or q_d^i with $i \in \{F, M\}$ occurs) and thereby the risk of undesirable outcomes is described by the probability p^i for upside scenarios (with q_u^i) and $(1 - p^i)$ for downside scenarios (with q_d^i) with $i \in \{F, M\}$ via a binomial distribution.

Though different fashionable IT innovations are likely to be characterized by different probabilities regarding institutionalization, we for reasons of simplicity assume the probabilities p^i with $i \in \{F, M\}$ to be constant over time. Hence, p^i with $i \in \{F, M\}$ describes the possibility that an investment in *M* creates the desired cash flows (M^u with q_u^M) at $t = s + 1$ and $t = s + 2$ respectively, or, in case of F, becomes institutionalized at all at $t = s + 1$ and creates desirable cash flows at $t = s + 2$ (F^u with q_u^F). By means of $1 - p^i$ with $i \in \{F, M\}$ we describe the probability that an investment in *M* will create below-average cash flows (M^d with q_d^M) at $t = s + 1$ and $t = s + 2$ respectively or, in case of *F*, will turn out to be a failing technology at $t = s + 1$ with $CF_t^F = 0$. In case *F* became institutionalized at $t = s + 1$, $1 - p^F$ represents the probability that *F* will create below-average cash flows at $t = s + 2$ (F^d with q_d^F).

Assumption 7: The company is a risk-neutral decision maker who aims at maximizing the net present value (NPV) of the IT innovation portfolio's expected cash flows $E(CF_t^{PF})$. The expected cash flows are discounted to present with a constant risk-free interest rate $r \in [0,1]$.

Assuming a risk neutral decision maker is reasonable as the IT innovation portfolio's scope is to do basis research for discovering long-term value which oftentimes means dealing with riskier investments than, for example, an IT asset portfolio (Maizlish and Handler 2005; Ross and Beath 2002). However, we do not expect the general cause-and-effect relationships to change distinctively when modeling a risk-averse investor.

A fashionable IT innovation can turn out to be both, a failing technology and a groundbreaking technology. Therefore, its cash flows at $t = s + 1$ and $t = s + 2$ are of particular interest to the analysis (Fenn and Raskino 2008; Fichman 2004). Regarding the mature IT innovation, we also consider a downside as well as an upside scenario. According to our assumptions, investing in a fashionable IT innovation F or a mature IT innovation M at $t = s$ can result in the cash flows CF_t^F or CF_t^M given in Table 1.

Table 1. Scenarios for the IT innovation's cash flows.

Scenario	Cash flow for *F*	Cash flow for *M*
Upside scenario at $t = s + 1$ with probability p^i and $i \in \{F, M\}$	$(a_s^F \cdot ITIB)^{q_u^F} \cdot v_s^F$	$(a_s^M \cdot ITIB)^{q_u^M} \cdot v_s^M$
Downside scenario at $t = s + 1$ with probability $(1 - p^i)$ and $i \in \{F, M\}$	0	$(a_s^M \cdot ITIB)^{q_d^M} \cdot v_s^M$
Upside scenario at $t = s + 2$ with probability p^i and $i \in \{F, M\}$	$(a_{s+1}^F \cdot ITIB)^{q_u^F} \cdot v_{s+1}^F$	$(a_{s+1}^M \cdot ITIB)^{q_u^M} \cdot v_{s+1}^M$
Downside scenario at $t = s + 2$ with probability $(1 - p^i)$ and $i \in \{F, M\}$	$(a_{s+1}^F \cdot ITIB)^{q_d^F} \cdot v_{s+1}^F$	$(a_{s+1}^M \cdot ITIB)^{q_d^M} \cdot v_{s+1}^M$

To enable *ex ante* and *ex post* analyses on the engagement in fashionable IT innovations (i.e., the allocation of $ITIB$ at t to F), we in our objective function of the dynamic optimization problem determine the allocation of $ITIB$ that maximizes the IT innovation portfolio's expected NPV:

$$\max_{a_t^F} \sum_{t=0}^{n} \frac{-ITIB + E\left(CF_t^{PF}\right)}{(1+r)^t} \quad s.t. \tag{6}$$

$$0 \leq a_t^F \leq 1 \text{ and } v_t^F = v_{t-1}^F \cdot M_{t-1}(a_{t-1}^F) \tag{7}$$

After describing the particular IT innovation investment strategy problem with possible scenarios, cash flows for different periods and the objective function, we in the following evaluate and analyze the model. Thereby, in contrast to Häckel, et al. (2013b) and Häckel et al. (2017) who use similar assumptions and just focus on an *ex ante* perspective, within our analyses we evaluate various investment strategies both from an *ex ante* and an *ex post* perspective.

II.3.4 Model Evaluation

We solve this dynamic optimization problem on the basis of a decision tree with the different scenarios regarding the evolution of F and M and perform a roll-back (i.e. dynamic programming according to Bellmann (1957) analysis (Suleyman 1993; Magee 1964; Clemons and Weber 1990). For the evaluation we choose a planning horizon of 10 periods (comprising five innovation lifetime cycles with two periods each) as this makes it possible to perform a meaningful analysis of the organizational learning effect's influence over time and ensures reasonable computation runtimes at the same time. As evaluating our approach by means of real-world data is rather difficult, we analyze the optimal investment strategy both from an *ex ante* and an *ex post* perspective for a given parameter set and different scenarios. Within our model evaluation we focus on the influence of a company's initial ability to innovate on the advantageousness of different IT innovation investment strategies. According to Hevner et al. (2004) as well as Gregor and Hevner (2013), the analytical evaluation of an optimization model or the gathering of data by simulation are legitimate means in IS research. Table 2 shows the parameter values which are relevant for the analysis. Analogous to Kauffman and Li (2005) we take $r = 0.1$ for the risk-free interest rate and $v_t^{M^*} = 100$ for the company's individual innovator profile regarding mature investments. We generally conduct our analysis with rather conservative values to avoid distortion due to overoptimistic value estimations.

Table 2. Simulation's parameter values.

Parameter	Value
Company's individual innovator profile v_0^F	50, 100 or 150
Fashionable IT innovation's impact factor q_u^F (upside scenario)	0.40
Mature IT innovation's impact factor q_u^M (upside scenario)	0.30
Probability that fashionable IT innovation will create desirable cash flows p^F	0.10
Probability that mature IT innovation will create desirable cash flows p^M	0.15
Average engagement of the market α^F	0.05
Periodical IT innovation budget B	50
Maximal periodical growth rate of the innovator profile β	0.20
The learning effect's proportionality factor k	10
Global upper limit for a company's innovator profile G	250

II.3.4.1 Ex ante analysis of the optimal investment strategy in fashionable and mature IT innovations

First of all, we analyze the optimal investment strategy depending on a company's initial innovativeness. Given the parameter setting and the justifiable assumptions mentioned above, our first finding is that the optimal engagement a_t^F in fashionable IT innovations dynamically changes over time and furthermore increases with the company's initial innovativeness. For a below-average innovative company (with $v_0^F = 50$) the optimal engagement a_t^F in fashionable IT innovations increases from 28.2% in $t = 0$ to 41.8% at the end of the planning horizon of ten periods. Similar results can be observed for an average innovative company (with $v_0^F = 100$) and an above-average innovative company (with $v_0^F = 150$) for which the optimal engagement rises from 38.6% to 59.4% and from 45.2% to 59.3% respectively. This increase over time can be explained by organizational learning through engagement in fashionable IT innovations which improves a company's future ability to innovate with IT. Despite this theoretical finding, different industries in practice often adopt fixed IT innovation investment strategies for different kinds of (IT) innovations that do not vary over time (Nagji and Tuff 2012; Ross and Beath 2002). Transferred to our IT innovation investment model this means, that a_t^M is constant over the complete planning horizon. As a consequence, such fixed strategies that are comparable to naive rules of diversification in financial portfolio theory by nature differ from the company's individual optimal investment strategy and in particular do not consider the effect of organizational learning.

To estimate the potential loss in NPV induced by such fixed investment strategies, we compare the *ex ante* expected NPV that results from applying the optimal dynamic strategy with the *ex ante* expected NPV resulting from the best fixed strategy (i.e. the fixed strategy with the highest NPV). Thereby, we assume that a company is able to determine this best fixed strategy based on experience or a profound gut feeling decision. Figure 2 clearly shows that the NPV of the optimal dynamic investment strategy always exceeds the NPV of the best fixed investment strategy, regardless of a company's innovativeness. This difference in NPVs would even be significantly larger for a 'random' fixed investment strategy based on an inaccurate gut feeling decision. The NPV thereby always comprises the investments in fashionable as well as mature IT innovations.

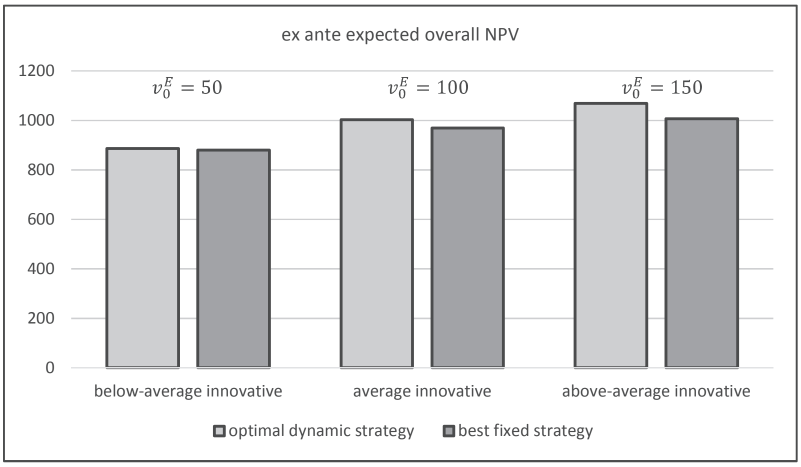

Fig. 2. *Ex ante* expected overall NPVs from a dynamic or fixed investment strategy in fashionable and mature IT innovations for companies with different innovativeness.

Furthermore, two interesting facts can be observed by taking a closer look at Fig. 2. First, it is fairly surprising that the NPV of the optimal dynamic strategy of an above-average innovative company exceeds the overall NPV of the optimal dynamic strategy of a below-average innovative company by merely 20.5% (1068 vs. 886) although we assume that the value of

v_0^F is three times higher for an above-average company. This under proportional increase can be explained by the fact that in our model companies benefit from a higher innovativeness only through investments in fashionable IT innovations. As mature IT innovations on the other hand are better understood and best practices are already available, more innovative companies cannot gain significant competitive advantages through investing in mature IT innovations. Hence, the moderate influence of a company's innovativeness on the expected NPV is plausible. Second, the relative difference in NPVs between the optimal dynamic and the best fixed investment strategy is relatively small. For a below-average innovative company the optimal dynamic strategy exceeds the best fixed strategy by only 0.7%. For an average innovative and an above-average innovative company, the difference in NPVs rises to 3.5% and 6.2 % respectively. The observed increase in difference between the two strategies can be explained by the fact that the influence of organizational learning increases with a higher initial innovativeness. As a consequence, for a more innovative company it is particularly beneficial to dynamically adjust its investment strategy over time due to the effects of organizational learning. In contrast, companies with a low initial innovativeness would need an extremely high engagement in fashionable IT innovations to significantly increase their innovativeness through organizational learning which in general does not pay off within the considered planning horizon. Thus, such companies usually adjust their investment strategy considerably less over time.

To sum up, our analysis reveals that the optimal dynamic investment strategy dominates the best fixed investment strategy with respect to the expected NPV regardless of a company's innovativeness. Although the difference is relatively low for this comparison, a similar analysis with a 'random' fixed strategy would show a significantly higher difference between the NPVs of the two investment strategies. Therefore, such a comparison would raise even more convincing arguments for an optimal dynamic investment strategy. According to our analysis, an optimized dynamic investment strategy seems to offer considerable benefits from an *ex ante* perspective with respect to the expected NPV.

In the next paragraph we analyze how the optimal dynamic strategy performs in selected, realized scenarios from an *ex post* perspective. Once again, we compare this strategy to the best fixed investment strategy to investigate, which strategy turns out to be superior for the selected scenarios from an *ex post* perspective. Thereby, we in particular focus on the volatility of the NPV in the selected scenarios.

II.3.4.2 Ex post analysis of the optimal investment strategy in fashionable and mature IT innovations

In order to compare the two different investment strategies mentioned above from an *ex post* perspective we use a backtesting approach and so evaluate the *ex ante* determined investment strategies within specific scenarios. As the evaluation of the large variety of different possible scenarios would be extremely comprehensive and the demonstration of the most essential cause-and-effect-relationships is also possible based on a couple of scenarios, we reduced the number of analyzed scenarios to six. Furthermore, we solely backtested the fashionable IT innovation as this type of innovation investment is in the focus of our analysis. The scenarios with five consecutive institutionalizations (5U) and five consecutive failures of the fashionable IT innovation (5D) should be part of the analysis to investigate how the two strategies perform in such extreme constellations. Furthermore, we take the scenarios of three institutionalizations and two failures (3U2D) as well as three failures and two institutionalizations (3D2U) into consideration. In order to consider the sequence of the realization we moreover added the scenarios of alternating institutionalization and failure (UD and DU, respectively).

Initially, we calculate the NPV from the investments in fashionable IT innovations resulting from the *ex ante* determined optimal dynamic strategy. This calculation was conducted for the six *ex post* scenarios outlined above and for a below-average innovative, an average innovative and an above-average innovative company each. In addition, we evaluate the same for the best fixed investment strategy and illustrate the results in Fig. 3.

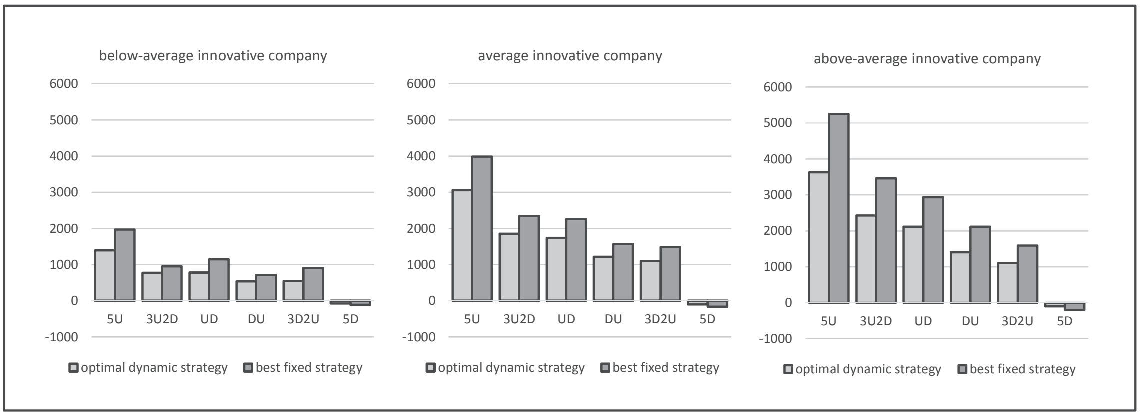

Fig. 3. Fashionable NPVs from a dynamic or fixed investment strategy for six backtesting scenarios clustered by companies with different initial innovativeness.

Comparing the NPVs regarding the different levels of innovativeness, Fig. 3 clearly shows a significant growth of all NPVs with increasing innovativeness. This finding is reasonable and obvious, as the initial innovativeness significantly influences the cash flows generated by the investment in fashionable IT innovations. We obtain a more interesting result when comparing the optimal dynamic investment strategy with the best fixed investment strategy. Regardless of a company's innovativeness, the fixed investment strategy generates significantly higher NPVs for five of the six scenarios. In the sixth scenario (5D) the NPVs for both strategies apparently are negative as the fashionable IT innovation never becomes institutionalized and thus no positive cash inflows are generated at all. By taking a closer look at this concrete scenario, however, we can observe that the optimal dynamic strategy leads to a smaller negative NPV as the fixed strategy.

At a first view, these results contradict with the results from paragraph 4.1 where we showed that the optimal dynamic strategy dominates the best fixed investment strategy with regard to the expected NPV. However, this first impression is misleading due to the highly unequal probabilities of the six scenarios. Considering the probability of success of $p^F = 10\%$ for the fashionable IT innovation, the 5D scenario is by far the most likely scenario. As the optimal dynamic strategy dominates the fixed strategy in this scenario, also its dominance regarding the expected NPV becomes obvious. Table 3 shows the probabilities for all of the six scenarios.

Table 3. Probabilities of occurrence for the different scenarios.

Scenario	5U	3U2D	UD	DU	3D2U	5D
Probability	0.001 %	0.081 %	0.081 %	0.729 %	0.729 %	59.049 %

In order to get an unbiased view for the specific scenarios, the NPVs from Fig. 3 are weighted with their probability of occurrence and illustrated in Fig. 4.

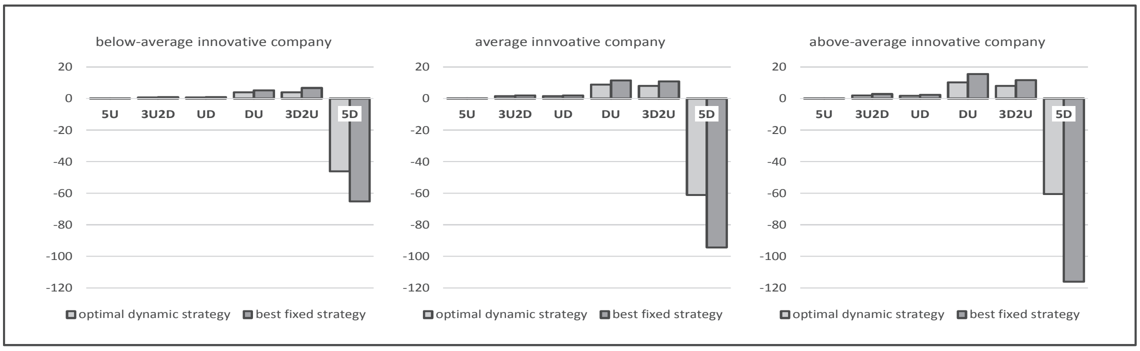

Fig. 4. Fashionable NPVs from a dynamic or fixed investment strategy for six backtesting scenarios weighted by the probability of occurrence and clustered by companies with different initial innovativeness.

Due to the weighting, the different scenarios are now comparable and in contrast to Fig. 3 it immediately gets clear that the 5D scenario is the most relevant one as the probability weighted NPV for this scenario dominates all other scenarios. Fig. 4 also demonstrates the dependence between the NPV and the level of initial innovativeness (see also Fig. 3) as the absolute NPVs rise with increasing initial innovativeness. This increase in absolute NPVs consequently leads to a higher spread between the NPVs of the different scenarios. Considering an above-average innovative company, for instance, the spread between the NPVs of the 5D scenario and the NPVs of the 3D2U scenario is considerably larger than for a below-average innovative company (both for the NPVs of the optimal dynamic investment strategy and the best fixed investment strategy). Therefore, when interpreting this volatility of NPVs as a risk measure an above-average innovative company’s optimal strategy is associated with more risk than an average innovative company’s or a below-average innovative company’s investment strategy. An analogue conclusion can be drawn by comparing the optimal dynamic strategy to the best fixed strategy over all levels of innovativeness. Regardless of how innovative a company is, the absolute NPVs generated from the optimal dynamic investment strategy are always smaller than the NPVs generated from the best fixed investment strategy. As this also implies a lower spread between the NPVs of the different scenarios for the optimal dynamic investment strategy, this strategy can be considered as less risky for the company.

To sum up the model evaluation, we clearly showed that the best strategy according to our optimization model outperforms even the best fixed investment strategy which maybe was just a good guess based on a gut feeling decision. In Sec. 4.1 we worked out that the optimal dynamic investment strategy leads to a higher expected NPV resulting from the investments made in fashionable and mature IT innovations. In conjunction with the lower volatility and therefore lower risk as seen in Sec. 4.2, the optimal dynamic investment strategy is superior compared to the best fixed investment strategy provided that expected NPV and volatility of NPVs are the relevant criteria. Finally, risk-neutral and risk-averse companies are thereby always better off by applying the optimal dynamic investment strategy in fashionable and mature IT innovations.

II.3.5 Theoretical and Practical Implications and Limitations

Decisions on IT innovation investments often do not follow a thorough *ex ante* analysis that considers changes in a company's innovativeness due to organizational learning. Our model aims at providing deeper insights in how a theoretically optimal IT innovation strategy is influenced by the development of a company's innovativeness over time. We thus contribute to IT innovation and organizational literature by developing a dynamic optimization model that firmly considers a company's initial and future innovativeness and by analyzing the results from an *ex ante* and *ex post* perspective. Thereby, the optimal allocation of a periodical IT innovation budget to different types of IT innovations can be determined. However, such a theoretically optimal allocation in practice hardly can be implemented due to management's uncertainty, missing data or political reasons. Companies thus often apply rather fixed IT innovation strategies which neglect the effect of organizational learning over time (Nagji and Tuff 2012; Ross and Beath 2002). Taking our theoretical model including its justifiable but also arguable assumptions as well as our *ex ante* and *ex post* analyses, our results make us suggesting the following propositions as a basis for further research and practice:

From an *ex ante* perspective (corresponding to Research Questions 1 and 2):

- A company's optimal allocation to fashionable and mature IT innovations depends on a company's ability to innovate and furthermore, the overall expected NPV from this engagement increases with a company's ability to innovate.
- Independently from a company's innovativeness, the optimal dynamic investment strategy dominates any fixed investment strategy with regard to the expected NPV of the investment.

From an *ex post* perspective (corresponding to Research Questions 3 and 4):

- A high innovative company's optimal dynamic investment strategy is associated with more volatility and therefore risk than a low innovative company's optimal dynamic investment strategy.
- An optimal dynamic investment strategy is associated with less volatility and therefore risk than the best fixed investment strategy — regardless of the company's innovativeness.

Our model aims at providing insights and propositions which might be the basis for further research approaches that are focused on empirically validating our findings. In a second step the empirical findings could be operationalized in a model that allows for concrete decision support in order to deliver valuable support for business problems. For that, the following aspects which are not covered yet by our approach need to be addressed: Though modeling organizational learning via a learning-by-doing approach is suitable to receive first results, the modeling of learning from communities or fashion-setting networks might provide additional insights. Furthermore, the model's inherent interpretation of the IT innovation's value is limited to quantifiable components of value. In addition, we only make a statement about the risk based on the volatility of *ex post* NPVs and do not integrate that aspect into the optimization model yet. Moreover, we simplify by not differentiating between innovation laggards, opportunistic adopters and systematic innovators which might require a more nuanced view on the engagement. Nevertheless, the model provides a basis for companies to gain insights into the characteristics of fashionable IT innovations which might support the evaluation of their IT innovation strategy.

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III Evaluation of Investments in IT Considering Financial Constraints

III.1 Research Paper 4: "Bewertung und Planung von IT-Investitionen unter Berücksichtigung finanzieller Beschränkungen."

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Published in:	Proceedings der 13. Internationalen Tagung Wirtschaftsinformatik (WI2017), St. Gallen, Schweiz.

Abstract:

Große Investitionen in Informationstechnologie (IT) sind oftmals langfristig geplante Investitionsvorhaben, die sich über einen längeren Zeitraum erstrecken und dadurch Investitionsauszahlungen in mehreren Perioden erfordern. Bei deren Planung und Budgetierung muss daher ein mehrperiodiger Planungshorizont inklusive relevanter finanzieller Rahmenbedingungen und Risiken berücksichtigt werden. Dadurch können Höhe und Zeitpunkt der Investitionsauszahlungen über mehrere Perioden hinweg optimal bestimmt und der erhoffte Wertbeitrag des Investitionsvorhabens abgesichert bzw. ggf. sogar gesteigert werden. Dies gilt insbesondere für Unternehmen, deren verfügbare finanzielle Eigen- und Fremdmittel stark begrenzt bzw. besonders unsicher sind. Deshalb sollten bei der Planung von langfristigen IT-Investitionen sowohl aktuelle, als auch zukünftig drohende finanzielle Beschränkungen berücksichtigt werden. Dies erfordert einen Disziplinen-übergreifenden Ansatz, der Erkenntnisse aus Finanzmanagement und IT-Management verbindet. In diesem Beitrag wird daher ein Optimierungsmodell entwickelt, bei dem relevante finanziellen Rahmenbedingungen bei der Planung eines IT-Investitionsvorhabens berücksichtigt werden, wodurch dessen Wertbeitrag gesteigert werden kann.

III.1.1 Einleitung und Motivation

IT-Investitionen sind durch die zunehmende Durchdringung von Unternehmen mit IT und die rapide fortschreitende Digitalisierung ein entscheidender Wettbewerbsfaktor für Unternehmen. Sie leisten einen wichtigen Beitrag zum langfristigen wirtschaftlichen Erfolg eines Unternehmens. Gleichzeitig können Unternehmen allerdings gezwungen sein, aufgrund finanzieller Beschränkungen geplante Budgets für langfristige IT-Investitionen zu reduzieren (vgl. bspw. [15], [26], [35]). Dadurch kann ein Unternehmen die Rückflüsse aus dem jeweiligen Investitionsvorhaben nicht bzw. nicht in geplanter Höhe realisieren, wodurch der dazugehörige Wertbeitrag erheblich reduziert wird oder sogar ein negativer Wertbeitrag resultieren kann. Die finanzielle Situation eines Unternehmens spielt daher auch für das Management von IT-Investitionen eine entscheidende Rolle. Folglich ist eine Disziplinen-übergreifende Integration von IT-Investitions- und Finanzmanagement notwendig, um IT-spezifische und finanzielle Aspekte integriert berücksichtigen zu können [30]. Eine Kombination etablierter Ansätze verschiedener Disziplinen bietet die Möglichkeit neue Lösungen für unternehmerische Fragestellungen zu entwickeln – selbst ohne eine grundlegende Weiterentwicklung der Ansätze. Gleichzeitig wird eine wertvolle Grundlage geschaffen für weiterführende Arbeiten wie bspw. empirische Studien oder exemplarische Anwendungen und Weiterentwicklungen auf Basis von realen Daten.

Zur Bewertung der ökonomischen Potentiale von IT-Investitionen existieren zahlreiche, überwiegend empirische, Arbeiten (bspw. [4], [27], [38], [40]), die den Zusammenhang zwischen IT-Investitionen und unternehmerischem Erfolg untersuchen. Daneben existiert in der Literatur eine weitere Forschungsrichtung, in der auf Basis quantitativer bzw. finanzwirtschaftlicher Ansätze Methoden für eine risikointegrierte Bewertung von IT-Investitionen entwickelt und analysiert werden. Zur Berücksichtigung von IT-spezifischen Risiken erweitert bspw. [39] den allgemeinen Kapitalkostensatz um einen spezifischen IT-Risikozuschlag (WACC zu WACIT). [42] vermindern hingegen den stochastischen Kapitalwert der IT-Investitionen um einen IT-spezifischen Risikoabschlag. [41] und [21] betrachten in ihrer Arbeit insbesondere das Risiko durch stochastische Abhängigkeiten der IT-Investitionen.

In dieser Arbeit werden Ansätze des Investitions- und Finanzmanagements zur Berücksichtigung finanzieller Beschränkungen ([2], [13]) auf den Kontext der IT-Investitionsplanung übertragen und um eine entsprechende Risikobetrachtung erweitert.

Dabei ist es nicht originäres Ziel diese Ansätze weiter zu entwickeln. Vielmehr sollen bestehenden Ansätze auf eine Problemstellung in einem anderen Kontext übertragen und entsprechend angepasst werden, um neue Lösungsmöglichkeiten zu entwickeln. Dadurch ist es möglich, finanzielle Rahmenbedingungen bei der Bewertung und Planung von langfristigen IT-Investitionen zu berücksichtigen. Mit Hilfe des entwickelten Optimierungsmodells kann gezeigt werden, dass der erwartete Wertbeitrag abgesichert bzw. sogar erhöht werden kann, wenn auf finanzielle Beschränkungen mit einer Liquiditäts- bzw. Budgetreserve – welche in der Finanz- bzw. Investitionsliteratur als probates Mittel anerkannt ist ([5], [18]) – reagiert wird. Um die Auswirkungen einer solchen Reserve auf den Wertbeitrag des IT-Investitionsvorhabens zu quantifizieren, wird dieser *mit* und *ohne* Reserve ermittelt und werden beide Alternativen miteinander verglichen.

Dazu wird ein Modell zur Planung von IT-Investitionen entwickelt, mit dessen Hilfe für ein Unternehmen die in Bezug auf Investitionszeitpunkt und Höhe optimalen Auszahlungen in das IT-Investitionsvorhaben unter Berücksichtigung finanzieller Rahmenbedingungen bestimmt werden können. Da es sich um einen integrierten Ansatz handelt, der IT-Investitions- und Finanzmanagement verbindet, wird die zur Entwicklung des Modells relevante Literatur an den jeweiligen Stellen herangezogen, sodass die Literatureinbettung im Modellteil und nicht wie zumeist üblich in einem gesonderten Literaturkapitel erfolgt.

Danach werden grundlegende Einflüsse zentraler Faktoren auf den Wertbeitrag des Investitionsvorhabens diskutiert und auf Basis eines Fallbeispiels analysiert. Zuletzt werden die Ergebnisse und Limitationen des Beitrags zusammengefasst und ein Ausblick auf weiterführende Forschungsfragen und praxisrelevante Implikationen gegeben.

III.1.2 Modell und relevante Literatur

Zunächst werden die Annahmen für die Bewertung des IT-Investitionsvorhabens anhand der relevanten Literatur vorgestellt und darauf aufbauend für das betrachtete Unternehmen die optimalen Investitionsauszahlungen (bzgl. Zeitpunkt und Höhe) zur Erreichung des maximalen Wertbeitrags (WB) ermittelt. Um den Einfluss der finanziellen Rahmenbedingungen auf den WB zu verdeutlichen, wird darauffolgend der resultierende WB in deren Abhängigkeit analysiert.

III.1.2.1 Modellannahmen

Im Rahmen eines Zwei-Perioden-Modells wird ein Unternehmen betrachtet, das die für ein mehrperiodiges IT-Investitionsvorhaben verfügbaren finanziellen Eigen- und Fremdmittel mit Hilfe einer Reserve optimal auf zwei mögliche Investitionszeitpunkte aufteilen möchte (vgl. Abbildung 1).

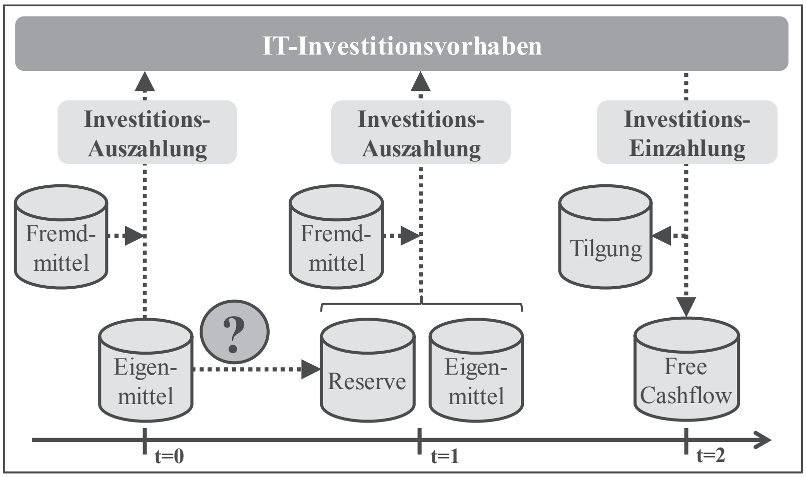

Abbildung 1. Entscheidungssituation des Modells.

Annahme 1) *Das Unternehmen verfügt in den Zeitpunkten $t = 0$ und $t = 1$ über die Cashflows $\widehat{CF}_t$ aus dem bestehenden Unternehmensportfolio, die für die IT-Investitionen verwendet werden können. $\widehat{CF}_0$ ist bekannt, wohingegen $\widehat{CF}_1$ unbekannt und gemäß $\widehat{CF}_1 \sim N\left(E[\widehat{CF}_1], \sigma^2(\widehat{CF}_1)\right)$ normalverteilt ist.*

Bei der Planung mehrperiodiger IT-Investitionsvorhaben ist es nicht ausreichend, nur für den gegenwärtigen Zeitpunkt die Investitionsauszahlungen zu planen, da deren Finanzierung über den kompletten Planungszeitraum hinweg sichergestellt sein muss. Andernfalls wir der insgesamt erwartete WB gefährdet, falls das Unternehmen zukünftige Investitionsauszahlungen nicht in ausreichender Höhe finanzieren kann.

Die Cashflows des Unternehmens stellen die Basis für die Planung der Investitionen dar. Dabei wird der zeitliche Horizont der Investitionen berücksichtigt, wobei sich Teilinvestitionen eines IT-Investitionsvorhabens in lang- und kurzfristige IT-Investitionen unterscheiden lassen (vgl. [24], [31], [43]). Dabei konkurrieren die Teilinvestitionen eines Investitionsvorhabens indirekt um begrenzte Unternehmensressourcen, wodurch sie sich gegenseitig beeinflussen und daher im Rahmen der IT-Investitionsplanung integriert betrachtet werden sollten [30].

Zur Finanzierung des Investitionsvorhabens kann das Unternehmen zusätzlich zu den Cashflows $\widehat{CF}_t$ auch Kredite aufnehmen und die für die Investition zu tätigenden Auszahlung I_t mit $t \in \{0,1\}$ dadurch erhöhen.

Annahme 2 a) *Im Zeitpunkt t nimmt das Unternehmen einen Kredit in Höhe von K_t mit $t \in \{0,1\}$ auf, welcher im Zeitpunkt $t = 2$ vollständig getilgt wird. Die mit dem risikolosen Zinssatz r_f anfallenden Zinsen sind zusammen mit der Tilgung im Zeitpunkt $t = 2$ endfällig zu zahlen.*

Insbesondere bei IT-Investitionen ist die Möglichkeit der Fremdfinanzierung allerdings oftmals stark eingeschränkt, da IT-Investitionen (bspw. die Entwicklung einer Software) i. d. R. zu einem hohen Anteil immateriell sind [22] bzw. mit Hilfe von IT-Investitionen unternehmensindividuelle, immaterielle Güter (bspw. Informationsverfügbarkeit und -qualität) geschaffen werden [10]. IT-Investitionen haben daher häufig einen spezifischen Wert für das jeweilige Unternehmen, der auch erhebliche immaterielle Investitionsbestandteile (bspw. aufgebautes Wissen) umfasst. Dieser unternehmensspezifische Wert ist durch den unternehmensspezifischen Wertanteil i. d. R. deutlich höher als ein rein anhand der Investitionsauszahlungen (I_t) feststellbarer objektiver Liquidationswert [11]. Darüber hinaus können IT-Investitionen bei einer kurzfristig notwendigen Liquidation nur mit erheblichen Preisabschlägen veräußert werden (falls überhaupt), da für ein anderes Unternehmen erneut erhebliche unternehmensspezifische Anpassungen erforderlich wären. Dadurch kann kurzfristig oftmals selbst der objektive Liquidationswert nicht erlöst werden.

Finanzielle Restriktionen dieser Art führen grundsätzlich zu einer Einschränkung der Investitionsfähigkeit eines Unternehmens [7], [12], [13]. Dies gilt insbesondere für IT-Investitionen, da deren hoher immaterieller Werteanteil die Aufnahme von Krediten zur Finanzierung der Investitionsauszahlungen erschwert [1], [20], [33]. Diese Besonderheit muss daher bei der IT-Investitionsplanung berücksichtigt werden, da dadurch die maximal finanzierbaren Investitionsauszahlungen begrenzt werden [1], [20], [33].

Annahme 2 b) *Die Höhe des Kredits K_t im Zeitpunkt $t \in \{0,1\}$ ist gemäß $K_t \leq \left(1 - \gamma_{I_t}\right) \cdot I_t$ beschränkt und hängt von der Höhe der Investitionsauszahlungen I_t des Unternehmens im jeweiligen Zeitpunkt ab. Dabei bezeichnet $\gamma_{I_t} \in (0,1)$ einen IT-investitionsspezifischen Illiquiditätsparameter.*

Der Illiquiditätsparameter γ_{I_t} bildet die beschränkte Fremdfinanzierungsmöglichkeit von IT-Investitionen ab. Die Höhe des Illiquiditätsparameters ist investitionsspezifisch, wobei bspw. ein erworbener Server (als standardisierte Hardware leichter übertragbar) i. d. R. mit einem geringeren Abschlag liquidiert werden kann als eine speziell entwickelte Individualsoftware (i. d. R. nur nutzbar für das jeweilige Unternehmen).

Um die verfügbaren Mittel optimal auf die periodischen Investitionsauszahlungen allokieren zu können, muss ein Unternehmen schätzen, wie die Höhe der erreichbaren Investitionseinzahlungen (d.h. die Rückflüsse der Investitionen) von der Höhe der Investitionsauszahlungen abhängt. Dadurch kann unter Berücksichtigung der geschätzten Grenzein- bzw. -auszahlungen der Wertbeitrag des IT-Investitionsvorhabens maximiert werden. Dazu muss ein Unternehmen das ökonomische Potential, d.h. die für das Unternehmen realisierbaren Einzahlungen, des IT-Investitionsvorhabens schätzen. Dabei ist zu berücksichtigen, dass verschiedene IT-Investitionen teilweise deutlich unterschiedliche ökonomische Potenziale aufweisen, die auch vom Investitionszeitpunkt und –umfang beeinflusst werden können. So weist bspw. eine frühzeitige Investition in eine IT-Innovation i.d.R. ein sehr hohes ökonomisches Potential auf, da sich dadurch bspw. neue Geschäftsfelder und Märkte erschließen lassen. Eine Investition in eine neue Verwaltungssoftware hat dagegen i.d.R. ein niedrigeres ökonomisches Potential, da sich damit zwar Effizienzgewinne erzielen lassen, diese aber oftmals deutlich geringer sind.

Zur Schätzung des Verhältnisses von monetären und nichtmonetären Inputgrößen zu Outputgrößen skalierbarer IT-Investitionen kann bspw. eine Funktion auf Grundlage der allgemeinen Produktionstheorie [37] verwendet werden (bspw. [8], [9], [16]). Solche Produktionsfunktionen finden bei der Planung von IT-Investitionen Anwendung [3], [22], wobei der dabei angenommene Zusammenhang i. d. R. nicht linear ist. Insbesondere bei großen IT-Investitionen sinkt mit steigendem Input der marginale Output, da mit steigendem Umfang die Komplexität und der Organisationsaufwand überproportional zunehmen [6], [22], d.h. die Einzahlungen sind oftmals durch abnehmende Grenzeinzahlungen gekennzeichnet.

Darüber hinaus lassen sich aufgrund der komplexen und vielfältigen Abhängigkeitsbeziehungen und Wechselwirkungen die Ein- und Auszahlungen von IT-Investitionen ex ante nur schwer abschätzen, weshalb diese mit einer großen Unsicherheit behaftet sind [16], [22]. Dabei tragen insbesondere die unsicheren Einzahlungen einer IT-Investition zu deren finanziellen Risiko bei [29], [34]. Zur Vermeidung von Fehlallokationen des IT-Budgets ist daher das Risiko bzw. die Unsicherheit der Einzahlungen von IT-Investitionen im Rahmen der IT-Investitionsplanung zu berücksichtigen [24].

Annahme 3) *Die im Zeitpunkt $t = 2$ durch die Investitionsauszahlungen für das Unternehmen ermöglichten Einzahlungsüberschüsse werden durch die Funktionen $EZ_i(I_t) = k_i \cdot f_i(I_t)$ mit $k_i \sim N(E[k_i], \sigma^2(k_i))$ mit $i = \{0,1\}$ abgebildet. Dabei bildet k_i das unsichere ökonomische Potenzial der IT-Investition ab und $f_i(I_t)$ sind streng monoton steigende und konkave Funktionen. Diese repräsentieren für das Unternehmen den Barwert aller in Abhängigkeit von den Investitionsauszahlungen I_t in der Zukunft realisierbaren Einzahlungsüberschüsse.*

Wie bereits beschrieben verringert die Unsicherheit über zukünftig verfügbare Eigen- und Fremdmittel die Investitionsfähigkeit eines Unternehmens [7], [12], [13]. Zur finanziellen Absicherung existieren verschiedene Methoden, wobei in dieser Arbeit das Vorhalten einer Reserve betrachtet wird, da viele Unternehmen bspw. nach [5], [18] hohe Summen als finanzielle Reserven vorhalten. Darüber hinaus ist bspw. eine Betrachtung von Kreditlinien im Rahmen der IT-Investitionsplanung nicht sinnvoll, da IT-Investitionen durch ihre hohe Illiquidität nur sehr eingeschränkt als Sicherheit verwendet werden können und mit Kreditlinien weitere Beschränkungen verbunden sind [12].

Annahme 4) *Das Unternehmen bildet in $t = 0$ eine (unverzinsliche) Reserve $R \geq 0$, welche in $t = 1$ zusätzlich für die Finanzierung der Investitionsauszahlung zur Verfügung steht.*

Das Unternehmen steht somit vor der Entscheidung, in welcher Höhe die aktuell verfügbaren finanziellen Mittel sofort investiert oder teilweise als Reserve für eine Absicherung der Investition in $t = 1$ vorgehalten werden sollen. Auf Basis der getroffenen Annahmen ergeben sich für das Unternehmen die folgenden Cashflows CF_t für $t \in \{0,1,2\}$, die die Grundlage für die Entscheidung bilden:

$$
\begin{aligned}
CF_0 &= \widehat{CF}_0 + K_0 - I_0 - R \\
CF_1 &= \widehat{CF}_1 + K_1 - I_1 + R \\
CF_2 &= EZ_0(I_0) + EZ_1(\tilde{I}_1) - K_0 \cdot \left(1 + r_f\right)^2 - K_1 \cdot (1 + r_f)
\end{aligned}
\tag{1}
$$

Dabei bezeichnet $CF_t \geq 0$ den nachschüssig anfallenden Free Cashflow, der für Ausschüttungen an die Eigenkapitalgeber zur Verfügung steht und die Grundlage für eine objektive Bewertung der IT-Investition bildet [19].

Um den Zeitwert der Zahlungen zu berücksichtigen, wird der Wert des Investitionsvorhabens zum Bewertungszeitpunkt $\mathrm{t} = 0$ mit Hilfe eines Discounted Cashflow-Verfahrens ermittelt [25]. Die Risiken der unsicheren Zahlungsüberschüsse können dabei mit Hilfe der Risikozuschlags- oder Risikoabschlagsmethode berücksichtigt werden, welche bei konsistenter Anwendung zu identischen Ergebnissen führen [14], [32]. Zur Bewertung mehrperiodiger Investitionen kann die Risikoabschlagsmethode verwendet werden [28], bei der ein Abzug eines Risikoabschlags von den erwarteten Free Cashflows gemäß $E[CF_t] - RA(CF_t)$ erfolgt. Der Risikoabschlag $RA(CF_t)$ wird dabei basierend auf dem Capital Asset Pricing Model (CAPM)[1] [17] multiplikativ mit Hilfe des Marktpreises des Risikos $\lambda = \frac{E[r_M]-r_f}{\sigma^2(r_M)}$ und der Kovarianz des Zahlungsüberschusses CF_t mit der Rendite r_M des Marktportfolios[2] $Cov(CF_t, r_M)$ ermittelt [23], [36]:

$$RA(CF_t) = \lambda \cdot Cov(CF_t, r_M) \tag{2}$$

Somit kann ein risikoadjustierter WB für den Zahlungsstrom der IT-Investition als Summe der auf den Zeitpunkt $t = 0$ mit dem risikolosen Zinssatz r_f diskontierten Cashflows abzüglich der jeweiligen Risikoabschläge berechnet werden. Dabei soll der erwartete WB durch die Wahl der optimalen Höhe der Investitionsauszahlungen I_t^* mit $t \in \{0,1\}$ maximiert werden, wodurch sich das folgende Optimierungsproblem ergibt:

$$\begin{gathered}\max_{I_t} WB = \sum_{t=0}^{2} \frac{E[CF_t]-RA(CF_t)}{\left(1+r_f\right)^t} = CF_0 + \frac{E[CF_1]-\lambda\cdot Cov(CF_1,r_M)}{1+r_f} + \\ \frac{E[CF_2]-\lambda\cdot Cov(CF_2,r_M)}{\left(1+r_f\right)^2} \\ CF_t \geq 0 \;\; \textit{für} \;\; t \in \{0,1,2\} \\ K_t \leq \left(1-\gamma_{I_t}\right)\cdot I_t \;\; \textit{für} \;\; t \in \{0,1\}\end{gathered} \tag{3}$$

Da im Optimum der Barwert der erwarteten Grenzzahlungsüberschüsse aus dem IT-Investitionsvorhaben dem Barwert der marginalen Investitionsauszahlungen entsprechen muss, können die optimalen Investitionsauszahlungen I_t^* folgendermaßen bestimmt werden:

[1] Es liegen keine Unsicherheit und intertemporalen Abhängigkeiten bzgl. der Verteilungsparameter vor, sodass eine mehrperiodige Anwendung des CAPM möglich ist.
[2] Das Marktportfolio enthält alle am Kapitalmarkt verfügbaren Vermögenswerte im Verhältnis zu ihrer Kapitalisierung.

$$\frac{\partial WB}{\partial I_0} = 0 \Leftrightarrow \frac{E[EZ_0'(I_0^*)] - \lambda \cdot f_0'(I_0^*) \cdot Cov(k_0, r_M)}{(1+r_f)^2} = 1 \ \textit{für} \ \ t = 0 \quad (4)$$

$$\frac{\partial WB}{\partial I_1} = 0 \Leftrightarrow \frac{E[EZ_1'(I_1^*)] - \lambda \cdot f_1'(I_1^*) \cdot Cov(k_1, r_M)}{(1+r_f)^2} = \frac{1}{(1+r_f)} \ \ \textit{für} \ \ t = 1 \quad (5)$$

Von I_t^* abweichende Investitionsauszahlungen vermindern den Wertbeitrag, da einerseits höhere Investitionsauszahlungen $(I_t > I_t^*)$ nicht durch die hieraus zusätzlich resultierenden risikoadjustierten Zahlungsüberschüsse kompensiert werden und andererseits niedrigere Investitionsauszahlungen $(I_t < I_t^*)$ weitere, noch mögliche Steigerungen des Wertbeitrags nicht realisieren.

III.1.2.2 Analyse des Modells

Im Folgenden wird die Investitionsstrategie eines Unternehmens analysiert, das finanziellen Beschränkungen unterliegt, d.h. es kann die eigentlich optimalen Investitionsauszahlungen I_t^* auf Grund von zu niedrigen bzw. zu unsicheren Cashflows $\widehat{CF}_t$ oder zu hohen Illiquiditätsabschlägen γ_{I_t} bei der Kreditaufnahme nicht finanzieren. Somit kann das Unternehmen selbst bei Verwendung aller zu den Investitionszeitpunkten $t \in \{0,1\}$ verfügbaren Mittel nur die geringeren *Investitionsauszahlungen eines finanziell beschränkten Unternehmens* $I_t^B < I_t^*$ finanzieren. Zur Maximierung des WB kann das Unternehmen mit Hilfe einer Reserve die Investitionsauszahlungen I_t^B mit $t \in \{0,1\}$ folgendermaßen optimieren:

Einerseits wird die Investitionsauszahlung I_0^B durch die Bildung der Reserve verringert und andererseits die Investitionsauszahlung I_1^B erhöht. Folglich verringert bzw. erhöht sich der resultierende Zahlungsüberschuss der jeweiligen Teilinvestition des Investitionsvorhabens. Je nachdem, welche Veränderung die höheren Auswirkungen hat, wird durch die Einzahlung in eine Reserve der insgesamt aus dem Investitionsvorhaben resultierende Wertbeitrag negativ oder positiv beeinflusst. Zur Maximierung muss daher die optimale Höhe der Reserve R^* bestimmt werden.

Das Unternehmen wird in beiden Investitionszeitpunkten alle verfügbaren Mittel investieren, weil die Investition höhere Grenzein- als -auseinzahlungen erwarten lässt, da $I_t^B < I_t^*$ für $t \in \{0,1\}$. Zusätzlich werden die Investitionen mit so hohen Krediten wie möglich finanziert um die Investitionsauszahlungen zu erhöhen. Somit ergibt sich I_0^B mit Hilfe von Annahme 2b) und Formel (1) folgendermaßen:

$$I_0^B = \frac{\widehat{CF}_0 - R}{\gamma_{I_0}} \tag{6}$$

Sie ist von der Höhe der verfügbaren finanziellen Mittel sowie von der Höhe der gebildeten Reserve abhängig. Analog dazu ist in $t = 1$ die Höhe der Investitionsauszahlung I_1^B ebenfalls von der Höhe der risikoadjustierten finanziellen Mittel und der Höhe der in diesem Zeitpunkt aufgelösten Reserve gemäß

$$I_1^B = \frac{E[\widehat{CF}_1] - \lambda \cdot Cov(\widehat{CF}_1, r_M) + R}{\gamma_{I_1}} \tag{7}$$

abhängig. Da in beiden Investitionszeitpunkten alle verfügbaren finanziellen Mittel investiert werden ($CF_0 = CF_1 = 0$), ist nur der resultierende Cashflow des Zeitpunkts $t = 2$ für die Bestimmung der optimalen Höhe der Investitionsauszahlungen relevant. Das Optimierungsproblem des Unternehmens lässt sich damit nach

$$\begin{aligned} \max_{I_t} WB^B = {} & \frac{E[k_0] \cdot f_0(I_0^B) - \lambda \cdot f_0(I_0^B) \cdot Cov(k_0, r_M)}{(1+r_f)^2} + \frac{E[k_1] \cdot f_1(I_1^B) - \lambda \cdot f_1(I_1^B) \cdot Cov(k_1, r_M)}{(1+r_f)^2} \\ & - \frac{(1-\gamma_{I_0}) \cdot (I_0^B) \cdot (1+r_f)^2}{(1+r_f)^2} - \frac{(1-\gamma_{I_1}) \cdot (I_1^B) \cdot (1+r_f)}{(1+r_f)^2} \end{aligned} \tag{8}$$

als Summe der risikoadjustierten Barwerte der erwarteten Zahlungsüberschüsse aus dem IT-Investitionsvorhaben abzüglich der Barwerte der Tilgung der aufgenommenen Kredite (inklusive Zinsen) abbilden.

Wie bereits erläutert hat die Reserve für das Unternehmen sowohl erhöhende, als auch verringernde Auswirkungen auf den Wertbeitrag. Daher werden so viele Mittel in die Reserve eingestellt, bis die marginale Erhöhung des WB (durch die höhere Investitionsauszahlung in $t = 1$) der marginalen Verringerung des Wertbeitrags (durch die geringere Investitionsauszahlung in $t = 0$) entspricht. Diese optimale Höhe der finanziellen Reserve R^* kann mit Hilfe der folgenden Bedingung bestimmt werden:

$$\left[E[k_0] \cdot f_0'(I_0^B) - \lambda \cdot f_0'(I_0^B) \cdot Cov(k_0, r_M) - (1-\gamma_{I_0}) \cdot (1+r_f)^2\right] \cdot \left(\frac{1}{\gamma_{I_0}}\right)$$

$$= \left[E[k_1] \cdot f_1'(I_1^B) - \lambda \cdot f_1'(I_1^B) \cdot Cov(k_1, r_M) - (1-\gamma_{I_1}) \cdot (1+r_f)\right] \cdot \left(\frac{1}{\gamma_{I_1}}\right) \Leftrightarrow$$

$$\Leftrightarrow \left[E[k_0] \cdot f_0'\left(\frac{\widehat{CF}_0 - R^*}{\gamma_{I_0}}\right) - \lambda \cdot f_0'\left(\frac{\widehat{CF}_0 - R^*}{\gamma_{I_0}}\right) \cdot Cov(k_0, r_M) - (1-\gamma_{I_0}) \cdot (1+ r_f)^2\right] \cdot \left(\frac{1}{\gamma_{I_0}}\right) \tag{9}$$

$$= \begin{bmatrix} E[k_1] \cdot f_1'\left(\frac{E[\widehat{CF}_1] + R^* - \lambda \cdot Cov(\widehat{CF}_1, r_M)}{\gamma_{I_1}}\right) \\ -\lambda \cdot f_1'\left(\frac{E[\widehat{CF}_1] + R^* - \lambda \cdot Cov(\widehat{CF}_1, r_M)}{\gamma_{I_1}}\right) \cdot Cov(k_1, r_M) - (1-\gamma_{I_1}) \cdot (1+r_f) \end{bmatrix} \cdot \left(\frac{1}{\gamma_{I_1}}\right)$$

Unter Berücksichtigung der marginalen Erhöhung bzw. Verringerung des WB kann ein finanziell beschränktes Unternehmen durch optimale Wahl der Höhe der finanziellen Reserve R^* den resultierenden WB maximieren. Diese Möglichkeit zur Maximierung besteht allerdings nur für ein Unternehmen, welches finanzielle Beschränkungen bereits bei der IT-Investitionsplanung berücksichtigt.

Um die Auswirkung der Reserve auf den WB zu quantifizieren, wird für ein finanziell beschränktes Unternehmen der WB mit optimaler Höhe der Reserve $WB_{R^*}^B$ (d.h. unter Berücksichtigung der finanziellen Beschränkungen im Rahmen der IT-Investitionsplanung) mit dem WB ohne Reserve $WB_{R=0}^B$ verglichen. Somit kann eine Wertbeitragssteigerung WBS_{R^*} als Differenz der beiden Wertbeiträge definiert werden:

$$WBS_{R^*} = WB_{R^*}^B - WB_{R=0}^B \geq 0 \tag{10}$$

Im Folgenden wird das Modell auf Basis einer exemplarische Anwendung analysiert, um die Effekte geänderter finanzieller Beschränkungen zu quantifizieren.

III.1.3 Exemplarische Anwendung des Modells

Die folgende exemplarische Anwendung hat zum Ziel, zentrale Wirkungszusammenhänge des Modells mit Hilfe von Sensitivitätsanalysen zu verdeutlichen. Dabei werden auch die für ein Unternehmen relevanten ökonomischen Auswirkungen einer Reserve veranschaulicht. Für die exemplarische Anwendung werden zunächst die optimalen Investitionsauszahlungen ermittelt – ohne und mit Berücksichtigung der finanziellen Situation des Unternehmens – und anschließend mittels der Sensitivitätsanalysen der Einfluss relevanter Parameter auf den resultierenden WB bzw. die mögliche WBS_{R^*} analysiert.

Da eine Evaluierung des Modells auf Basis von Realweltdaten noch aussteht, wird im vorliegenden Beitrag als erster Schritt eine Analyse auf Basis exemplarischer Werte bzw. Funktionen vorgenommen. Dabei wird von den in Tabelle 1 aufgeführten Funktionen ausgegangen, sodass sich durch Abzug der Risikokosten von den Einzahlungen und deren Optimierung anhand Formel (4) bzw. (5) optimale Investitionssauzahlungen I_t^* i. H. v. 55,47 bzw. 113,38 Geldeinheiten (GE) ergeben.

Tabelle 1. Einzahlungen, Risikokosten und optimale Investitionsauszahlungen

Zeitpunkt	$EZ_i(I_t)$[3]	$\lambda \cdot f_i(I_t) \cdot Cov(k_i, r_M)$	I_t^*
$t = 0$	$1 \cdot 100 \cdot ln(I_0)$	$2{,}67 \cdot 100 \cdot ln(I_0) \cdot 0{,}15$	55,47
$t = 1$	$1 \cdot 150 \cdot ln(I_1)$	$2{,}67 \cdot 150 \cdot ln(I_1) \cdot 0{,}075$	115,38

Über die zur Finanzierung der Investitionsauszahlungen verfügbaren Cashflows (d.h. Eigenmittel) liegen Schätzungen zur erwarteten Höhe und deren Risiko vor. Die eingeschränkte Kreditaufnahme ist durch den Illiquiditätsparameter γ_{I_t} abgebildet. Tabelle 2 enthält die entsprechenden Werte zur Höhe der in den Investitionszeitpunkten verfügbaren Eigen- und Fremdmittel.

Tabelle 2. Parameterwerte zur finanziellen Situation des Unternehmens

	$t = 0$	$t = 1$	$t = 2$
Bestehender Cashflow $\widehat{CF}_t$	20	20	20
Standardabweichung der Cashflows $\sigma(\widehat{CF}_t)$	-	10	15
Illiquiditätsparameter γ_{I_t}	0,5	0,9	-

[3] Die Funktionen bilden den Barwert aller zukünftig anfallenden Einzahlungsüberschüsse zum Zeitpunkt $t = 2$ ab.

Auf Basis der in den Investitionszeitpunkten beschränkten Eigen- und Fremdmittel plant das Unternehmen für den Zeitpunkt $t = 0$ mit 40 GE (vgl. Formel (6)) und für den Zeitpunkt $t = 1$ mit 15,55 GE (vgl. Formel (7)) als erwartete Mittel, die für das IT-Investitionsvorhaben zur Verfügung stehen. Mit diesen Werten, die deutlich unter den optimalen Investitionsauszahlungen liegen (vgl. Tabelle 1), kann nur ein erwarteter WB i. H. v. 497,79 GE erreicht werden (vgl. Formel (3)). Werden dagegen mit Hilfe einer Reserve verfügbare Mittel i. H. v. 9,96 GE von $t = 0$ auf $t = 1$ übertragen, so können Investitionsauszahlungen i. H. v. 20,05 GE in $t = 0$ und 26,2 GE in $t = 1$ finanziert werden, die ebenfalls deutlich unter den optimalen Investitionsauszahlungen liegen, aber einen höheren WB i. H. v. 528,07 GE (vgl. Formel (8)) ermöglichen.

Tabelle 3. Vergleich der Situation mit und ohne Reserve

	R^*	I_0^B	I_1^B	$WB_{R^*}^B$
Mit Reserve	9,96	20,05	26,2	528,07
Ohne Reserve	-	40	15,56	497,79

Ohne Reserve würde das Unternehmen in $t = 0$ einen zu hohen Betrag und in $t = 1$ einen zu niedrigen Betrag investieren. Die Reserve ermöglicht eine optimale Anpassung der Investitionsauszahlungen, wodurch eine Wertbeitragssteigerung WBS_{R^*} i. H. v. 30,28 GE (~ 6,1%) erreicht werden kann. Um zu verdeutlichen, wie WBS_{R^*} von den finanziellen Rahmenbedingungen beeinflusst wird, werden die folgenden Sensitivitätsanalysen durchgeführt.

III.1.3.1 Analyse des Cashflows aus dem Unternehmensportfolio in $t = 0$

Ist in $t = 0$ ein im Vergleich zu den Startwerten des Beispiels höherer Cashflow $\widehat{CF}_0$ verfügbar, werden die höheren Mittel auf die Investitionsauszahlung in diesem Zeitpunkt und die Reserve aufgeteilt. Je höher dabei $\widehat{CF}_0$ ist, desto höher ist auch die Einstellung in die Reserve, da das Unternehmen durch die Investitionsauszahlungen in $t = 1$ höhere Grenzeinzahlungen erreichen kann. Ohne Reserve würde der höhere Zahlungsüberschuss für die Investitionsauszahlungen in $t = 0$ verwendet werden, wodurch aufgrund der niedrigeren Grenzeinzahlungen nur ein geringerer WB erzielt werden könnte. Zur Veranschaulichung sind in Abb. 2 sind WBS_{R^*} und R^* in Abhängigkeit vom $\widehat{CF}_0$ abgebildet.

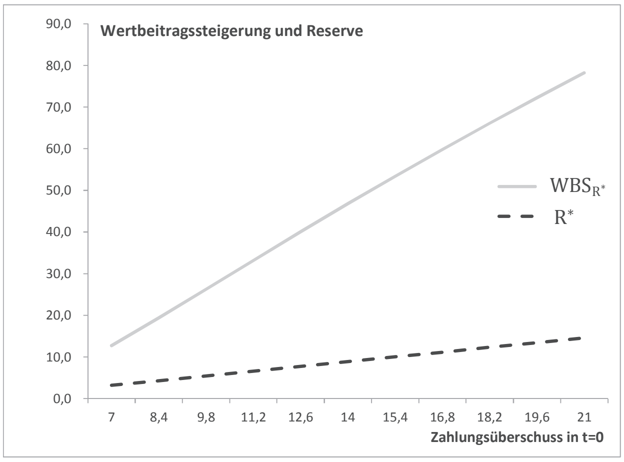

Abbildung 2. Einfluss der Höhe des Cashflows in $t = 0$

Der wertbeitragssteigernde Effekt der Reserve wird größer und eine höhere Reserve wird vorgehalten, je höher der in $t = 0$ verfügbare Cashflow $\widehat{CF}_0$ ist.

III.1.3.2 Analyse des Cashflows aus dem Unternehmensportfolio in $t = 1$

Erwartet das Unternehmen in $t = 1$ einen im Vergleich zu den Startwerten des Beispiels höheren Cashflow $\widehat{CF}_1$, kann die Höhe der Reserve verringert werden, da mehr Mittel zur Finanzierung der Investitionsauszahlung in $t = 1$ erwartet werden. Bei einem niedrigeren Cashflow $\widehat{CF}_1$ wird die Reserve dagegen erhöht, um die Investitionsfähigkeit in $t = 1$ abzusichern. Ohne Reserve kann das Unternehmen die verfügbaren Investitionsauszahlungen in $t = 1$ nicht erhöhen, obwohl eine höhere Investition vorteilhaft wäre, da sich in $t = 1$ höhere marginale Einzahlungen erreichen lassen. Die Wertbeitragssteigerung WBS_{R^*} wird daher auch überproportional größer, je niedriger der erwartete Cashflow $E\left[\widehat{CF}_1\right]$ ist (vgl. Abb. 3).

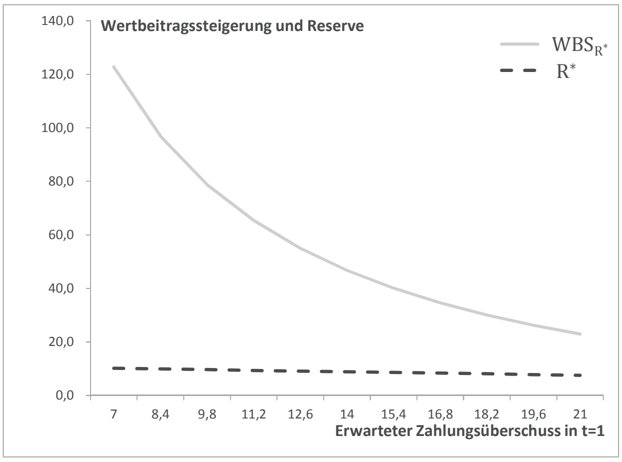

Abbildung 3. Einfluss der Höhe des erwarteten Cashflows in $t = 1$

Abb. 3 verdeutlicht, dass bei sinkendem erwarteten Cashflow $E[\widehat{CF}_1]$ durch eine Erhöhung der Reserve eine zunehmende Wertbeitragssteigerung WBS_{R^*} möglich ist.

III.1.3.3 Analyse des Risikos des Einzahlungsüberschusses in $t = 1$

Erhöht sich das Risiko des Cashflows $\widehat{CF}_1$ (d.h. $\sigma(\widehat{CF}_1)$) im Vergleich zu den Startwerten des Beispiels, sinken die verfügbaren risikoadjustierten Mittel in $t = 1$ durch die höheren Unsicherheit. Durch die Reserve kann dies bei der IT-Investitionsplanung berücksichtigt werden, sodass mehr Mittel für die Investition in $t = 1$ vorgehalten werden. Dabei steigt WBS_{R^*} wenn sich das Risiko des Cashflows $\sigma(\widehat{CF}_1)$ erhöht (vgl. Abb. 4).

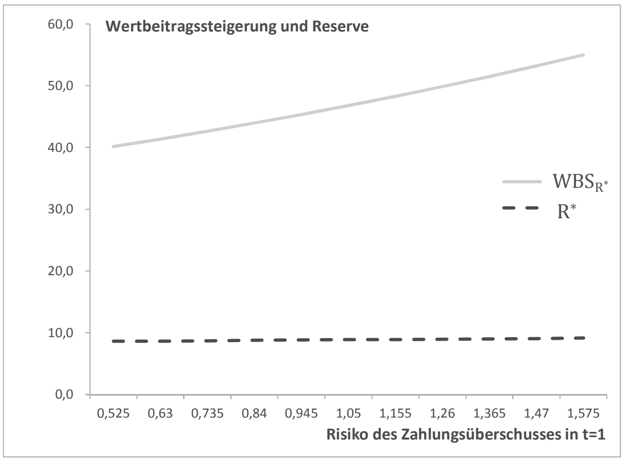

Abbildung 4. Einfluss des Risikos des Zahlungsüberschusses in $t = 1$

Insgesamt erhöht sich somit der Vorteil einer Reserve (gemessen durch WBS_{R^*}), je niedriger aktuelle und je höher zukünftige erwartete finanzielle Beschränkungen sind. Die Reserve hat somit einen hohen positiven Einfluss auf den WB von IT-Investitionen wenn ein Unternehmen gegenwärtig über hohe Mittel verfügt und davon einen Teil für Investitionen in zukünftigen Perioden vorhält, in denen die Finanzierung der geplanten Investitionsauszahlungen sehr unsicher ist.

III.1.4 Zusammenfassung und Ausblick

Durch finanzielle Beschränkungen besteht die Gefahr, dass langfristige IT-Investitionen eingeschränkt bzw. sogar kurzfristig abgebrochen werden müssen, wodurch ein Unternehmen deren geplanten WB nicht realisieren kann. Da die Relevanz von IT-Investitionen bspw. durch die voranschreitende Digitalisierung für Unternehmen verschiedenster Branchen weiter zunimmt und eine Berücksichtigung der finanziellen Rahmenbedingungen bei der Planung von solchen Investitionsvorhaben i. d. R. nicht ausreichend erfolgt, wurden in dieser Arbeit IT-Investitions- und Finanzmanagement in einen Ansatz integriert.

Mit dem entwickelten Modell können mit Hilfe einer finanziellen Reserve die negativen Auswirkungen finanzieller Beschränkungen verringert werden, da ein Unternehmen die Investitionsauszahlungen anpassen kann und dadurch der resultierende WB steigt. Zur Verdeutlichung des Einflusses der Reserve wurde die mögliche Wertbeitragssteigerung anhand eines Fallbeispiels analysiert. Dabei zeigen die durchgeführten Sensitivitätsanalysen, dass der wertbeitragssteigernde Effekt besonders deutlich ist, wenn ein Unternehmen aktuell über hohe Mittel verfügt und zukünftige Mittel geringer bzw. unsicher sind und dadurch die zukünftige Investitionsfähigkeit gefährdet ist. In diesem Fall kann durch die Reserve die langfristige Finanzierung des IT-Investitionsvorhabens abgesichert und dessen WB gesteigert werden.

Daher sollten Unternehmen bei der Budgetierung längerfristiger IT-Investitionsvorhaben nicht nur die Investitionsauszahlungen der aktuellen Periode optimieren, sondern auch zukünftige Investitionsauszahlungen berücksichtigen und deren Finanzierung absichern. Daher sollte eine Abstimmung zwischen Finanz- und IT-Abteilung erfolgen, damit die notwendigen Mittel zum richtigen Zeitpunkt zur Verfügung stehen. Dazu sollte ein langfristiges Optimierungskalkül zugrunde gelegt werden, bei dem neben IT-spezifischen Faktoren auch finanzielle Ertrags- und Risikoaspekte berücksichtigt werden. Auf dieser Basis können optimale langfristige Budgets bestimmt werden. Dabei sollte es einem IT-Projektmanager auch ermöglicht werden einen Teil des Budgets für Investitionsauszahlungen in Folgeperioden zu reservieren, ohne eine Budgetkürzung befürchten zu müssen.

Durch die getroffenen Annahmen und gewählten Parameter weist das Modell Schwächen bzw. Einschränkungen auf, die allerdings zugleich Raum für Erweiterungen im Rahmen zukünftiger Forschungsarbeiten bieten. So könnte für die Quantifizierung der Einzahlungen und Risiken Schätzverfahren entwickelt werden, die für verschiedene IT-Investitionen passende Funktionen auf Basis historischer Daten spezifizieren. Da der Fokus der Arbeit auf den finanziellen Aspekten der IT-Investitionen liegt, bleibt eine tiefergehende Analyse und Abbildung immaterieller Werte von IT-Investitionen künftiger Forschung vorbehalten. Da das auf bestehenden Ansätzen aufbaut und diese neu kombiniert, kann es keine fundamentale Weiterentwicklung dieser Ansätze leisten. Nichtsdestotrotz bietet das Modell einen Disziplinen-übergreifenden Ansatz, der im Rahmen weiterer Arbeiten empirisch validiert oder anhand eines realen Praxisbeispiels angewendet werden könnte (bspw. durch großzahlige empirische Untersuchungen oder Fallstudien).

Trotz der genannten Restriktionen kann der vorliegende Beitrag in einem ersten Schritt zeigen, dass eine Berücksichtigung finanzieller Rahmenbedingungen bei der Planung mehrperiodiger IT-Investitionen einen Beitrag zur Absicherung bzw. Erhöhung des resultierenden WB leisten kann.

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IV Evaluation of Energy Efficiency Investments Based on Different Theoretical Frameworks

IV.1 Research Paper 5: "Explaining the Energy Efficiency Gap – Expected Utility Theory versus Cumulative Prospect Theory."

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Published in:	Energy Policy, 111 (2017)

Abstract:

Energy efficiency is one of the key factors in mitigating the impact of climate change and preserving nonrenewable resources. Although environmental and economic justifications for energy efficiency investments are compelling, there is a gap between the observable and some notion of optimized energy consumption - the so-called energy efficiency gap. Behavioral biases in individual decision making have been resonated by environmental research to explain this gap. To analyze the influence of behavioral biases on decisions upon energy efficiency investments quantitatively, we compare Expected Utility Theory with Cumulative Prospect Theory. On basis of a real-world example, we illustrate how the extent of the gap is influenced by behavioral biases such as loss aversion, probability weighting and framing. Our findings indicate that Cumulative Prospect Theory offers possible explanations for many

barriers discussed in literature. For example, the size of the gap rises with increased risk and investment costs. Because behavioral biases are systematic and pervasive, our insights constitute a valuable quantitative basis for environmental policy measures, such as customer-focused and quantitatively backed public awareness campaigns, financial incentives or energy savings insurances. In this vein, this paper may contribute to an accelerated adaption of energy efficiency measures by the broader public.

IV.1.1 Introduction

One of the key factors in mitigating the impact of climate change and preserving non-renewable resources is energy efficiency (EE). Recent sweeping environmental policy advances aim to drastically increase EE to combat global climate change. In its "Energy Roadmap 2050", the European Commission, by 2050, aims to reduce energy consumption of existing building stock by 80% relative to 2010 levels (European Commission, 2012). Thereby, investments in EE measures for buildings are one of the European Commission's focus as the building stock is responsible for 40% of energy consumption and 36% of CO2 emissions in the EU (European Commission, 2017). Furthermore, the European Commission has set EE as one of its main objectives ("putting energy efficiency first") and wants to accelerate building renovation rates (European Commission, 2016). Likewise, the U.S. Department of Energy has announced a massive program to promote EE (Department of Energy, 2015). The environmental and economic justifications for investing in EE are compelling. According to Granade et al. (2009), energy consumption in the U.S. could be reduced as much as 23% by 2020 with cost-effective measures. Furthermore, most related theoretical work has stressed the economic cost-effectiveness of corresponding EE measures. However, and despite its widely asserted profitability, there seems to be an EE gap between the observable use of energy and some notion of optimized use (Rosenfeld et al., 1993; Brown et al., 1998). The EE gap, also called the EE paradox, is defined as the phenomenon that, although EE investments "seem to present clear economic and environmental advantages, the level of investment in them does not reach the levels which would correspond to such benefits" (Linares and Labandeira, 2010, p.575–76). The aim of this study is to quantitatively compare the prevailing explanations of the EE gap based on rational decision-makers with explanations based on insights about psychological biases in decision-making.

IV.1.1.1 Explanations for the EE Gap

Most of the explanations of this EE gap are based on standard neoclassical theory. In this vein, market failures, like environmental externalities, or imperfect information are identified as the main barriers to EE investments. From this point of view, decision-makers make rational decisions that maximize individual expected utility. In the context of EE choices, these decisions involve investments optimizing the result of the tradeoff between higher initial investment costs and increasing energy savings, depending on uncertain future energy expenses. Given perfect information and correct prices, it is assumed that the decision-maker perfectly and rationally processes information to maximize expected utility. However, the rationality framework is not able to encompass all possible explanations for the EE gap and several researchers have seriously questioned the assumption of a rational decision-maker. In this way, those in behavioral economics propose that individuals are prone to a multitude of systematic biases that affect decisions in pervasive ways (Barberis, 2013). The specifics of EE investments, such as long-time horizons and high uncertainty about future savings, contribute to behavioral biases in individual decision-making. Many psychological biases are attributable to EE investments and are cited as good explanations for the EE gap (Greene, 2011). Yet, while recent environmental policy literature often states the importance of behavioral biases, it mainly discusses these issues just qualitatively. For meaningful policy conclusions, however, a quantification of such behavioral effects might offer valuable information regarding the ecological and economic potential of possible measures. One approach to capture such behavioral effects in a quantitative model is the well-known Prospect Theory (PT) of Kahneman and Tversky (1979). To quantitatively analyze the influence of behavioral biases when deciding upon EE investments, we compare a rational Expected Utility Theory (EUT) decision-maker with a PT decision-maker who decides upon perceived value.

IV.1.1.2 Cumulative Prospect Theory as a quantitative model for explaining the EE gap

Despite the call for the use of quantitative models that are not based on expected utility (non-expected utility models) for environmental policy analysis (Shaw and Woodward, 2008), so far, the application of PT to the case of EE investments is virtually absent. To describe the behavior of decision makers, and, in particular, to capture different systematic behavioral biases, PT mainly comprises four elements (Barberis, 2013; Kahneman and Tversky, 1979):

(1) *Reference dependence*: Decision-makers utility is described by reaction to changes in wealth (gains and losses) related to their current reference point (typically the status quo) rather than upon total wealth. Henceforth, outcomes evaluated relative to a reference point will be prefixed with a Δ.

(2) *Loss aversion*: Decision-makers value the impact of losses bigger than that of gains.

(3) *Diminishing sensitivity*: Decision-makers are risk-averse in the domain of gains but risk seeking in the domain of losses. Thereby, with growing distance from the reference point, the impact of an outcome diminishes.

(4) *Probability weighting*: Decision-makers weight the probabilities of the outcomes instead of using statistical probabilities and underweight average events (center of the distribution), but overweight events with low probabilities (tails of the distribution).

As PT is mainly applicable to individual decision-making, the focus of this paper is on private decisions. Therefore, as a real-world application we analyze a prototypical EE investment in the weatherization of an owner-occupied residential building. This kind of investment bears

significant potential for EE through improved insulation of the building envelope, while the costs for achieving the energy savings are relatively low (Jakob, 2006). Nevertheless, the level of investment still seems to fall below the optimal level (Granade et al., 2009). In this context, we apply Cumulative Prospect Theory (CPT), which was introduced by Tversky and Kahneman (1992) as an advancement of the original PT to overcome the possible violation of first-order stochastic dominance. Thereby CPT allows for an explicit quantification of many well recognized behavioral biases and enables a comparison with EUT.

While much research on the EE gap has stressed the importance of behavioral economics, to date empirical and quantitative theoretical work on CPT and its elements in the context of EE investments is scarce. Therefore, the contribution of our paper is threefold: First, to the best of our knowledge, we are the first to implement all elements of CPT to quantitatively evaluate EE investments. In particular, we show how CPT can be applied to analyze EE investment decisions quantitatively based on a Net Present Value (NPV) approach. Second, we analyze if and to what extent, CPT can explain the EE gap, and the main parameters influencing it. Therefore, we use CPT to evaluate the distribution of possible NPVs of an EE investment as compared to EUT in order to deliver first quantitative evidence on the contribution of CPT to explaining the EE gap. Third, as our approach enables a thorough analysis and quantification of behavioral biases, we help to make behavioral biases addressable and correctible by environmental policy measures. Even though, we provide micro-level insights into the decision-making of an individual EE investor, the results from this paper support policy makers in generating incentives that accelerate the adoption of EE technologies on macro-level.

The remainder of this paper is organized as follows. In Section 2, we review research on the EE gap and barriers to investing in EE. Thereby, we put a focus on behavioral barriers. Section 3 includes descriptions of EUT and CPT in order to evaluate EE investments. This is followed by a discussion of specifics of EE investments, and how these are depicted within a NPV approach outlined in Section 4. The simulation analysis and its results are presented and discussed in Section 5. Finally, the conclusions and contributions to literature (and practice) are discussed in Section 6.

IV.1.2 The Energy Efficiency Gap

In a very general form, Jaffe and Stavins (1994a, p.804) refer to the E gap as “the paradox of gradual diffusion of apparently cost-effective energy-efficiency technologies”. Brown (2001, p.1198) defines the EE gap as “the difference between the actual level of investment in energy efficiency and the higher level that would be cost-beneficial from the consumer's (i.e., the individual's or firm's) point of view”. Thus, in our context, we define the EE gap as the difference between observable investments in EE and a cost-effective level of EE investments that would be optimal from the perspective of a EUT decision-maker. Estimates for the size of the EE gap are wide ranging, but there is substantial empirical evidence for its existence. There are three streams in literature that indicate the existence of the EE gap based on different approaches: (1) macro-level engineering-economic studies (see e.g., Brown et al., 1998; Granade et al., 2009; Rosenfeld et al., 1993). The basic approach in such studies is to calculate the NPV of possible EE measures given assumed capital costs, energy prices, investment horizons, and discount rates (Allcott and Greenstone, 2012). (2) Case studies for specific products and technologies, which show that consumers and firms often choose not to invest in highly cost-effective EE measures (DeCanio and Watkins, 1998; Gates, 1983; Koomey and Sanstad, 1994; Koomey et al., 1996; Meier and Whittier, 1983). And (3) a large part of the evidence on the EE gap is based on analyses of implicit discount rates. Numerous studies report the observation that consumers use high implicit discount rates in making EE investment decisions (Dubin and McFadden, 1984; Gately, 1980; Hausman, 1979; Min et al., 2014; Ruderman et al., 1987). However, sometimes the existence of the EE gap is viewed skeptically. For example, Allcott and Greenstone (2012) state that the EE gap is possibly only in the range of about 1–2% of energy use. Nevertheless, the majority of authors indicate that energy markets are full of barriers that could explain the EE

gap.

IV.1.2.1 Barriers to EE investments

Generally, barriers to EE investments represent factors that limit the diffusion of cost-effective EE measures (Vine et al., 2003). There are two main kinds of barriers to EE investments: (1)

structural barriers and (2) behavioral barriers (Brown 2001; Hirst and Brown 1990; Shogren and Taylor 2008; Weber 1997).

IV.1.2.1.1. Structural Barriers

Structural barriers "result from the actions of many public- and private-sector organizations and are primarily beyond the control of the individual end-user" (Hirst and Brown, 1990, p. 269). Literature distinguishes between market-failures and non-market failures.

Market failures occur when there is a deviation from the way perfect markets operate (Brown, 2001). Commonly reported market failures are associated with externalities (Brown, 2001; Gillingham et al., 2009; Jaffe et al., 2004), imperfect information (Allcott and Greenstone, 2012; Howarth and Andersson, 1993; Linares and Labandeira, 2010), innovation market failures (Coltrane et al., 1986; Jaffe and Stavins, 1994b;) and imperfect capital markets (Blumstein et al., 1980; Brown, 2001; Gillingham et al., 2009).

Non-market failures refer to obstacles that explain why observed behavior is indeed optimal from the point of view of individual energy users (Brown, 2001; Hirst and Brown, 1990; Jaffe and Stavins, 1994a). Its main point is the riskiness of EE investments (Hassett and Metcalf, 1993; Metcalf, 1994; van Soest and Bulte, 2001) and barriers within institutions and organizations (Brown, 2001; DeCanio, 1993; De Groot et al., 2001; Hirst and Brown, 1990; Lovins, 1992; Weber, 1997).

Structural barriers and environmental policies derived predominantly from market-failures are usually based on a rational human actor in the sense of neoclassical theory (Gintis, 2000). This presupposes that consumers and firms act in their self-interest, based on full information and rational calculus of cost, benefits, and risk to maximize expected utility. Despite its preeminence in economic models, the rationality hypothesis is often blamed for being an inadequate representation of actual human behavior. Many of the market and non-market failures to EE investments can also be traced back to individual decision-making that is prone to behavioral barriers (Shogren and Taylor, 2008; Stern, 2011; Wilson and Dowlatabadi, 2007).

IV.1.2.1.2. Behavioral Barriers

Generally, behaviors with regards to energy conservation can be separated into efficiency and curtailment behaviors (Barr et al., 2005; Gardner and Stern, 2002). Curtailment behaviors comprise repetitive 'habitual' behaviors in the context of energy usage, such as lowering thermostat settings. Efficiency behaviors relate to a single decision about the investment in an EE measure, also called 'technology choices'. Much of the existing empirical research has focused on curtailment behaviors (e.g., Abrahamse et al., 2005). For instance, more recently, Alcott and Rogers (2014) examined a program to induce energy conservation by providing information, financial incentives as well as social comparison on basis of home energy reports. Empirical research on efficiency behavior is mainly focused on socio-economic analysis of purchasers of EE measures (e.g., Barr et al., 2005; Gaspar and Antunes, 2011; Sütterlin et al., 2011). For owners of detached houses in Sweden, Nair et al. (2010) introduced several determinants, which they categorize into contextual factors and personal factors.[1] Further, empirical research on efficiency behavior often analyses the influence of ex ante provision of information to potential investors in EE measures. For example, Fowlie et al. (2015) found high non-monetary costs related to information acquisition. However, in this paper, we focus on behavioral barriers to EE that affect investment decisions even in the in reality unlikely case of perfect information. Thus, we start from a decision-maker able to observe and aggregate future outcomes, but failing to rationally process this information due to behavioral barriers.

Such behavioral barriers are inside the individual and characterize decision-making (Hirst and Brown, 1990; Weber, 1997). Behavioral barriers imply that a decision-maker fails to behave as predicted by EUT (Stern, 2011). The existence of behavioral economics has been substantiated by evidence that decision-makers are not perfectly rational. Even if they are given perfect information, they often systematically deviate from neoclassic economic assumptions of rationality (Kahneman and Tversky, 1979). There exist persistent biases in individual decision-making that result in behavior not consistent with such rationality assumptions (Camerer et al., 2004; DellaVigna, 2009).

In energy literature, a wide range of research has demonstrated that assumptions of economic rationality regarding the behavior of energy users, and their investment decisions, are fundamentally flawed (Frederiks et al., 2015; Gillingham and Palmer, 2014; Gintis, 2000; Shogren and Taylor, 2008; Stern, 2011). Even having perfect information, decision-makers may not be able or motivated to make the complex calculus required to take the best decision.

[1] In Nair et al. (2010) contextual factors include homeownership, building age, need for thermal comfort, previous investments in EE, perceived energy costs and geographical location. Personal factors include education, income, age, gender, (technical) skill, awareness about EE measures and attitude.

For instance, Kempton and Montgomery (1982) showed that energy consumers systematically deviate from cost minimizing behavior even when motivated to make careful decisions. Thus, early on, energy experts promoted the study of the social and psychological aspects of energy use as well as the psychological barriers to EE investments (Coltrane et al., 1986; Stern and Aronson, 1984). Knetsch (1997, p.209) argued that "in view of the evidence, the seemingly quite deliberate avoidance of any accounting of these (behavioral) findings in the design of environmental policy or in debates over environmental values, does not appear to be the most productive means to improvement". Further, Gintis (2000) asserted that individual decision-making systematically violates prevailing axioms of decision theory in the context of environmental policies. In particular, individuals are prone to the status quo bias, and exhibit time inconsistent preferences with regards to the evaluation of future costs and benefits[2]. Wilson and Dowlatabadi (2007) reviewed models of decision making in the residential energy context. As examples of irrational choice, they analyzed time inconsistency, framing, reference dependence, and bounded rationality. They concluded that the key findings of behavioral economics are observable in the real world. Gowdy (2008, p.632) "takes the position that so-called behavioral "anomalies" are central to human decision-making and, therefore, should be the starting point for effective economic policies". Frederiks et al. (2015), Pollitt and Shaorshadze (2013), Shogren and Taylor (2008), and Stern (2011) provided exhaustive summaries on the contributions of psychology to the understanding of human behaviors that drive climate change and human reactions to EE technologies. They concluded that psychological factors are important determinants of EE related behaviors and "also influence the acceptance and implementation of public policies to limit climate change and the adoption of low-carbon energy technologies" (Stern, 2011, p.311). Some authors also presented evidence on how behavioral failures might cause underinvestments in EE and thus cause the EE gap. For instance, Masini and Menichetti (2012) developed and tested a conceptual model that examined the behavioral factors affecting financial investment decisions in renewable energy technologies.

[2] While time inconsistent preferences constitute an important insight into human decision making (see e.g., Frederick et al., 2002, Laibson, 1997), in this paper we assume a decision maker exhibiting time consistent preferences modeled with a NPV approach (also see Section 4). We do so for two reasons: First, our approach is based on the socalled method of risk analysis, which was underpinned from a decision-theoretical point of view in Bamberg et al. (2006). Accordingly, in a first step, periodical cash flows are aggregated to NPVs preference-free. Then, these NPVs are evaluated preference-based using a specific utility function. Second, we exclusively analyze the effects of all CPT elements as compared to EUT. Considering additional elements not covered by CPT, such as time inconsistency, may distort our findings and impede the analyses.

So far, we can conclude that previous literature has provided substantial evidence underlining that EUT should not be the only model to guide environmental decision-making. Despite this evidence, incorporation of non-expected utility models into the environmental economics literature has been relatively slow (Shaw and Woodward, 2008). One of the best-known models of non-expected utility is PT (Barberis, 2013). Kahneman and Tversky (1979) introduced a critique of EUT and developed an alternative model called PT, which is based on empirical (psychological) evidence and describes how decision-makers choose between a set of risky alternatives. PT incorporates many well researched behavioral biases and its elements are widely cited as possible explanation for the EE gap in the literature on behavioral environmental economics (e.g., Gintis, 2000; Gowdy, 2008; Shogren and Taylor, 2008; Stern, 2011; Wilson and Dowlatabadi, 2007). However, it is striking that, to the best of our knowledge, there is almost no research that aims to explain the EE gap by employing PT quantitatively or empirically. One exception is Mayer (1995) who empirically examined consumer rationality as compared to PT for electricity conservation. His findings support "the efficacy of prospect theory over utility maximization for consumer investment in electricity saving equipment" (Mayer, 1995, p.109). However, Mayer only provided indirect evidence for the EE gap and did not investigate all elements of PT. Moreover, Greene (2011) applied certain elements of PT in a quantitative model to account for uncertainty and loss aversion. His model was used to examine the influence of uncertainty and loss aversion in the application scenario of increased fuel economy of new passenger cars. The author concluded that the examined implementation of PT "can explain the observed tendency for markets to undervalue energy efficiency improvements to new equipment relative to their expected value" (Greene, 2011, p.616). However, the model did not incorporate all elements of PT (such as probability weighting). Thus, the aim of this study is to explain the EE gap by comparing an EE investment decision based on EUT with respect to CPT as an advancement to PT, depicting both rational decision-makers and decision-makers that decide upon perceived value. By means of such an explicit calculation, it is possible to draw quantifiable conclusions on the influence of behavioral barriers to the EE gap. This enables effective, consumer-focused policy making to improve EE. Therefore, in the next section, we will compare EUT with CPT regarding the evaluation of EE investments.

IV.1.3 Evaluation of EE Investments

Standard neoclassical theory is based on the assumption that decision-

makers behave rationally and make investment decisions that

maximize their expected utility. Accordingly, EUT is a normative theory and investigates how decisions under risk should be made rationally.[3] With decisions under risk, a formal representation of the decision problem is possible:

$$EUT = \sum_{i=1}^{n} p(x_i) \cdot u(\varphi_i), \tag{1}$$

where n is the number of outcomes x_i, $p(x_i)$ is the objective probability of outcome x_i and $u(\varphi_i) = u(\varphi_o + x_i)$ is the individual utility of total wealth φ_i, which is the initial wealth φ_0 plus outcome x_i.[4] When the resulting EUT value is larger than initial utility $u(\varphi_0)$ then the investment is utility enhancing and should be executed.

In our analysis, however, we assume an investor, who decides upon the perceived value of an EE investment. PT was designed for individual decision-making and is not quite applicable to company-level decision-making (Shogren and Taylor 2008).[5] Thus, we analyze an individual PT decision-maker who evaluates an EE investment exhibiting reference dependence, loss aversion, diminishing sensitivity and probability weighting (see Section 1.2).

To capture the described properties when evaluating a stochastic outcome Δx_i, Kahneman and Tversky (1979) suggested a value function $v()$ and a weighting function $w()$ that transform the outcomes and the probabilities compared to EUT. The first three elements described in Section 1.2, concerning a single outcome Δx_i, are implemented in the so-called value function:

[3] EUT is based on three main principles: (1) the overall expected utility of a choice is the expected utility of the distribution of possible outcomes. (2) It exists a utility function $u()$ that represents the risk profile of an investor and can be used to value uncertain future outcomes x_i. (3) A choice is acceptable if it adds utility to the existing assets.

[4] In a more general form Expected Utility is defined as $E[u(\tilde{X})]$, where $\tilde{X}$ is a random variable. When $\tilde{X}$ is discretely distributed, Eq. (1) can be applied to compute the value of Expected Utility.

[5] The decisions of corporate managers on EE investments are (e.g., because of their high investment volume) usually preceded by intense discussions in several committees. PT may not be applicable to this comparatively rational organizational decision-making process. However, it may be applicable in a corporate context when corporate governance mechanisms are weak (Wen, 2010) or if the contextual factors of the organization are considered (Shimizu, 2007).

$$v(\Delta x_i) = \begin{cases} (\Delta x_i)^{\alpha} & \Delta x_i \geq 0 \\ -\lambda \cdot (-\Delta x_i)^{\beta} & \Delta x_i < 0 \end{cases}, \tag{2}$$

with $\alpha = \beta = 0.88$ being the weighting-factors that determine the curvature for the positive (α) and negative domain (β), as originally specified in Kahneman and Tversky (1979). The parameter $\lambda = 2.25$ captures loss aversion, expressing that decision-makers consider losses more than twice as important as gains. Fig. 1 schematically illustrates the value function with the reference point as its origin.

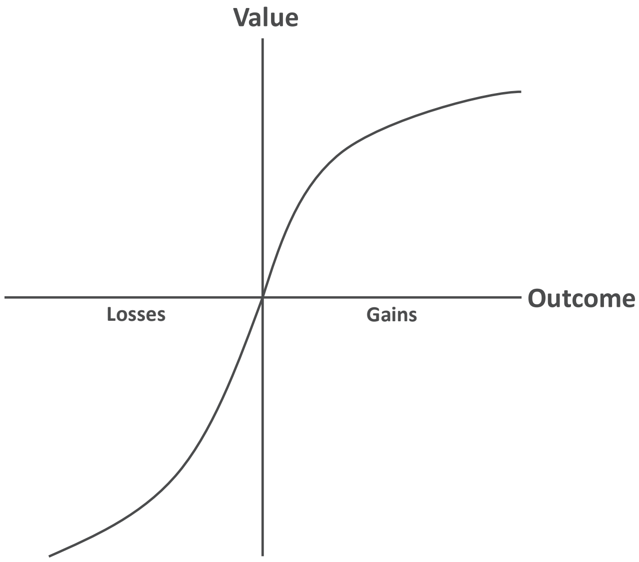

Figure 1: A hypothetical value function according to Kahneman and Tversky (1979).

However, the value function alone insufficiently describes human value perception. Decision behaviors such as buying insurance contracts (risk-averse loss perception) and gambling (risk-seeking gain valuation) contradict the results of the value function. Thus, instead of weighting the subjective values according to Eq. (2) with their objective probabilities, Tversky and Kahneman (1992) introduced the probability weighting function:

$$w(p(\Delta x_i)) = \begin{cases} \frac{p(\Delta x_i)^{\gamma}}{(p(\Delta x_i)^{\gamma} + (1 - p(\Delta x_i))^{\gamma})^{1/\gamma}} & \text{for } \Delta x_i \geq 0 \\ \frac{p(\Delta x_i)^{\delta}}{(p(\Delta x_i)^{\delta} + (1 - p(\Delta x_i))^{\delta})^{1/\delta}} & \text{for } \Delta x_i < 0 \end{cases}. \tag{3}$$

The weighting function rescales objective probabilities $p(\Delta x_i)$ to perceived probabilities $w(p(\Delta x_i))$ consistent with the concept of diminishing sensitivity. Thereby, $\gamma = 0.61$ and $\delta = 0.69$ are the factors that distinguish between the domain of gains and losses, and mainly control curvature. A multitude of studies have validated this functional form (e.g., Gonzalez and Wu 1999; Lattimore et al. 1992).[6] However, because first-order stochastic dominance is potentially violated in the original PT, implying that a prospect might be evaluated superior although it yields an inferior outcome with certainty, an advancement was suggested by Tversky and Kahneman (1992). While single probabilities $p(\Delta x_i)$ are weighted in the original PT, cumulative probabilities are weighted in CPT. After cumulative probabilities have been weighted according to Eq. (3), the differences in neighboring probability weightings are computed to derive the decision weight π_i for each outcome:

$$\pi_i = \begin{cases} w(p(\Delta x_i) + \cdots + p(\Delta x_n)) - w(p(\Delta x_{i+1}) + \cdots + p(\Delta x_n)) & \text{for } \Delta x_i \geq 0 \\ w(p(\Delta x_1) + \cdots + p(\Delta x_i)) - w(p(\Delta x_1) + \cdots + p(\Delta x_{i-1})) & \text{for } \Delta x_i < 0 \end{cases}, \quad (4)$$

where all outcomes Δx_i are sorted in ascending order and $p(\Delta x_i)$ is the objective probability of the i-th outcome. Furthermore, it is valid for $\Delta x_i < 0$: $2 \leq i \leq k$ and for $\Delta x_i \geq 0$: $k + 1 \leq i \leq n - 1$, where k is the number of negative outcomes. Following Tversky and Kahneman (1992), the decision weight related to a positive outcome ($\Delta x_i \geq 0$) is the difference between the weighted cumulative probabilities of the events "the outcome is at least as good as Δx_i" and "the outcome is strictly better than Δx_i". Correspondingly, the decision weight related to a negative outcome ($\Delta x_i < 0$) is the difference between the weighted cumulative probabilities of the events "the outcome is at least as bad as Δx_i" and "the outcome is strictly worse than Δx_i" (Tversky and Kahneman 1992, p.301). Finally, given the decision weights π_i and the value weights $v(\Delta x_i)$, the CPT value of an EE investment is calculated as:

$$CPT = \sum_{i=1}^{n} \pi_i \cdot v(\Delta x_i), \quad (5)$$

where n is the number of possible outcomes. This results in the final CPT value, which is the perceived value of the distribution of outcomes that results from the EE investment for the individual decision-maker. Similar to EUT, a value greater than zero results in a favorable decision towards the EE investment. However, the CPT value may not be mistaken for a monetary value.

[6] However, there is also some literature that discussed shortcomings of the single parameter probability weighting function (e.g., Ingersoll, 2008). For example, Dichtl and Drobetz (2011) applied the probability weighting function suggested by Lattimore et al. (1992) that includes an additional parameter for elevation.

Although CPT focuses on one-period outcomes rather than on longterm investment decisions, the functional form of the perceived value is not restricted to one-period outcomes (e.g., Camerer and Ho, 1994; De Giorgi and Hens, 2006; Fennema and Wakker, 1997; Wakker, 1989). However, the value of a long-term investment requires consideration of the status quo, aggregation of future outcomes, and consideration of the time value of money. We will consider those issues in the next section by introducing a multi-period NPV approach considering the status quo of the decision-maker. Thus, in the following, the outcome Δxi previously inserted in the value function will be replaced with an outcome for the NPV of the EE investment.

IV.1.4 NPV Approach to Model EE Investments

An EE investment is similar to any other investment in real assets, as it reflects an initial financial expenditure followed by a subsequent, usually uncertain payoff (Sutherland, 1991). In this context, NPV analysis is the most commonly used investment evaluation method in EE literature (see e.g.: Ådahl and Harvey, 2007; Amstalden et al., 2007; Clinch and Healy, 2001; Johnson, 1994; Morrissey et al., 2013; Rickard et al., 1998). In line with these works, we also apply NPV analysis to determine whether the present value of future energy savings surpasses the initial investment costs of the EE investment.

As future energy savings of EE investments are uncertain, the resulting NPV will be risky. To account for this risk and to depict risk preferences of investors, we value the risky NPVs by applying EUT and CPT. Thus, in the first step, we use the NPV method to aggregate the cash flow structure of the EE investment in a well-established and economical recognized way. In the second step, we apply EUT and CPT to analyze possible differences for the case that the risky NPV is either valued by a purely rational decision maker, or by a decision maker exhibiting behavioral biases.

Thereby, as argued in Section 2.1.2, we assume a decision-maker able to observe and aggregate future outcomes in an economically reasonable way (i.e., by calculating the respective NPV), but failing to rationally process this information due to behavioral barriers. With regards to the aggregation of future outcomes it is often stressed that human preferences are dynamically time inconsistent by behavioral economics in general (Frederick et al., 2002; Laibson, 1997; Loewenstein and Thaler, 1989; Thaler, 1981) and for investments in EE in particular (Frederiks et al., 2015; Gillingham and Palmer, 2014; Gintis, 2000; Wilson and

Dowlatabadi, 2007). However, in this paper we exclusively focus on the comparison of EUT with CPT assuming intertemporal choice based on time consistent preferences as in standard NPV analysis. Thus, to obtain undistorted results and analyses, we do not consider additional elements that are not covered by CPT, such as time inconsistency.

The general form of the NPV calculation is:

$$NPV = -I_0 + \sum_{t=1}^{T} \frac{CF_t}{(1+r)^t}, \tag{6}$$

where I_0 is the initial investment cost of the EE investment at the time of decision $t = 0$. The time horizon T is usually set equal to the lifetime of the EE investment, the customer's expected useful life of the EE investment, or a subjective payback period of the EE investment (Thompson 1997). The time value of money is considered by discounting with the (risk-free) interest rate. The cash flow CF_t with $t \in \{1, \ldots, T\}$ includes the income in period t that results from the EE investment during its time horizon T. Income in this setting is the cash flow from future energy savings that results from the EE investment each period. To determine the savings of period t, we use the following calculation:

$$CF_t = P_t \cdot F_c \cdot \varepsilon \cdot M + UCB_t. \tag{7}$$

where P_t is the stochastic price per unit of energy (e.g., kWh) for period t. F_c depicts the current consumption of units of energy and ε is the energy savings. If the EE investment results in 20% savings in energy, then it holds $\varepsilon = 0.2$. Furthermore, the usage rate M accounts for an increase or decrease in energy use that is triggered by the Rebound Effect (Allcott and Greenstone 2012). The unobservable costs and benefits UCB_t comprise items of expenditure and co-benefits in period t that are not directly observable or hard to measure. For instance, increased thermal insulation may increase well-being and health, but the identification and quantification of UCB_t are subject to considerable methodological issues (e.g., Clinch and Healy 2001). We also do not account for costs of financing, such as interest rate payments; thus, we assume full equity financing.

However, investments typically do not provide fixed future periodical cash flows. Future cash flows rather depend on risky future developments (Johnson, 1994) and thus, the NPV of an investment is also risky. Risk in our model is primarily associated with uncertainty about future fuel prices Pt, because the development of energy price paths cannot be predicted. Consequently, only the periodical distribution or possible range of the EE investment's cash flows can be determined (Johnson, 1994). Thus, the investor has to evaluate the risk inherent in the resulting distribution of possible NPVs.

IV.1.5 Simulation Analysis

In the subsequent sections, the introduced decision framework is applied to the case of energy-efficient refurbishment of private homes in the German market (see Fig. 2 for an overview of the approach). For this analysis, first, we utilize information about energy consumption, EE potential, and investment costs, mostly obtained from a comprehensive study by the Institute for Housing and Environment (Enseling et al., 2013)[7]. Second, we simulate future energy prices with help of Monte-Carlo simulations in order to achieve a realistic representation of possible future real world prices (cf. Section 5.1). Third, we calculate resulting cash flows and the distribution of possible NPVs based on the future energy prices (cf. Section 5.2). Fourth, we apply the EUT and CPT framework described in Section 3 to evaluate the resulting NPVs (cf. Section 5.3). Finally, we compare and analyze the evaluation results (cf. Section 5.4).

[7] The "Institut Wohnen und Umwelt", the Institute for Housing and Environment, is a well-recognized and non-profit research institute of the State of Hesse and Darmstadt in Germany. Its research areas are housing, energy, and integrated sustainable development. The data of the study by Enseling et al. (2013) is based on cost functions derived from actual costs charged for energy-efficient refurbishment. The financial magnitude of costs and savings is in line with other research in this area. For example, based on an empirical study, Jakob (2006) quantifies the marginal costs of EE investments for the Swiss residential sector and finds results in comparable magnitude. However, we do not further elaborate on the data of Enseling et al. (2013), because it merely serves as a baseline of our exemplary calculation and the input combinations of investment costs and energy savings will be widely varied.

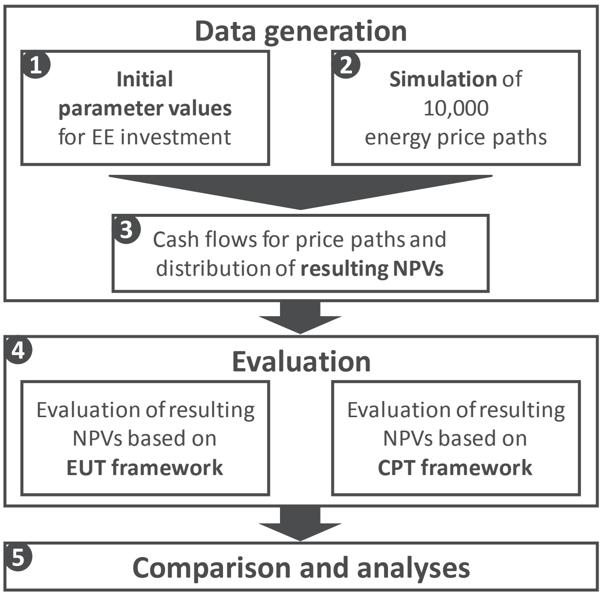

Figure 2: Approach for the analysis.

For our analysis, we refer to a model single-family detached house based on the German building typology (c.f. Table 1). This kind of house resembles a large portion of the German building stock (DENA, 2012) and has great potential for EE measures because of the low energy standards at the time of construction. It is assumed that the considered building is in possession of the owner-occupier and will not be sold at the end of the time horizon T. We start our analysis by running Monte Carlo simulations of domestic fuel oil prices.

Model single-family house (current state)	
Age class:	1919-1948
Net dwelling area:	163m²
Energy source (heating):	Domestic fuel oil
Final energy demand: radiator:	208 kWh/m²a
Final energy demand: hot water:	33 kWh/m²a

Table 1: Model house's main specifications based on Enseling et al. (2013).

IV.1.5.1 Monte Carlo Simulation

As described in Section 4, the price of energy is one of the most relevant sources of uncertainty for EE investments (Diederen et al. 2003; Greene 2011; Hassett and Metcalf 1993). Thus, in a first step, we assume the domestic fuel oil price P_t to be the source of risk. However, by varying the initial parameters of the EE investment (e.g., the investment costs I_0 and savings ε) a thorough analysis of further sources of risk is feasible. In the analysis at hand, the price of domestic fuel oil follows a geometric Brownian motion (GBM). This process has the desirable feature that forecast uncertainty increases with forecast horizon, and that extended periods of low and high energy-costs are observable. When modeling energy-price developments in such a way, there are two important parameters: (1) the long-term trend μ and (2) the degree of randomness around this trend σ. In formal terms, we model the GBM of P_t as:

$$\delta P_t = \mu P_t dt + \sigma P_t dz, \tag{8}$$

where dz is the increment to a Wiener process that describes the evolution of a standardized normally distributed variable with mean zero and unit variance. Thus, energy costs are rising linearly at trend rate μ, but exhibit substantial randomness around the trend. The parameter σ determines the degree of randomness and can be interpreted as the volatility of the energy price. We generate prices on a yearly evaluation period because many private investors evaluate their investments on a yearly basis (Benartzi and Thaler 1995) and energy costs are often calculated on an annual basis. Thus, $dt = 1$ resembles a single yearly increment. The stochastic process for domestic fuel price as depicted in Eq. (8) is a very common way to model commodity and energy prices and is widely used in EE investment literature (e.g., Ansar and Sparks 2009; Diederen et al. 2003; Hassett and Metcalf 1993).

Using the stochastic process in Eq. (8), we simulate 25 years of energy prices. To derive the full distribution of domestic fuel oil prices, we perform 10,000 simulation runs per year. The initial energy price per kWh (P_0), the long-term trend (μ), and volatility (σ), are specified using data from Enseling et al. (2013) that estimates the values from historical data and official studies. Thus, initially, we set the domestic fuel oil price $P_0 = 0.085€/kWh$, long-term price trend $\mu = 4.8\%$ and price volatility $\sigma = 20\%$. Later, the parameters are varied to evaluate their influence on the EE investment decision.

The simulated energy price paths provide the basis for the calculation of the cash flows CF_t and consequently the NPV_i. To obtain the NPV_i for each price path $i = 1 \; to \; 10{,}000$ with Eq. (6), the cash flows for all periods were computed with Eq. (7). Consequently, we derive the full distribution of NPVs of the EE investment.

IV.1.5.2 Calculation of NPVs

Enseling et al. (2013) distinguish between maintenance measures (such as refurbishment of the exterior wall) and EE-related measures (such as the thermal insulation of the building envelope). Usually such measures are carried out together. As this study focuses on EE investment decisions, the analysis only incorporates the costs and savings of the investment in EE related measures.

Based on the data of Enseling et al. (2013) which provided investment costs per square meter to achieve German energy standards[8], we derived investment costs per square meter net dwelling area. These comprise the costs of all energetic measures, which summed up to 31,133€, when looking at the EE investment alone.[9] However, these are only the investment costs I_0 for the baseline scenario. Later, a range of 10,000€ to 60,000€ will be analyzed. The energy savings ε that result from both, maintenance and EE investments, amount to about 65%. Obviously, this level of energy savings ε is too high when analyzing the savings of the EE investment alone, because it includes effects from maintenance measures as well.[10] To address this issue and enable analyses of various possible settings, in the further analysis we will vary ε in a broad range from 5% to 80%, but assume that it is constant over time (i.e., there is no stochasticity related to the energy savings obtained by the EE investment). Thus, to cover a broad variety of possible constellations, we analyzed combinations of investment costs I_0 ranging from 10,000–60,000€ and energy savings ranging from 5–80%. Table 2 summarizes the inputs to calculate the cash flows CF_t for every period $t = 1\ to\ T$ and every price path $i = 1\ to\ 10{,}000$. For reasons of simplicity and because it is not focus of this analysis, we assume that unobservable costs and benefits offset each other and hence $UCB_t = 0$. Initially, we assume that F_c, ε and M were constant over time. In this analysis, we do not account for a Rebound Effect, and thus, set $M = 1$. By discounting the future cash flows to present values with Eq. (6), we obtain NPV_i for all price paths $i = 1\ to\ 10{,}000$. The risk-free

[8] In particular, we consider as our baseline scenario an EE investment to achieve the KfW Efficiency House 100 standard, established by the German government-owned promotional bank KfW. This housing category conforms to the national energy standards laid out in the Energy Conservation Ordinance of 2007 (Energieeinsparverordnung/EnEV) that set limits to energy consumption and heat loss values for new buildings. The KfW promotes refurbishment of houses and, for example, the Efficiency House 100 may not exceed the values specified in EnEV 2007 by 100%

[9] For reasons of comparability and simplicity, we used prices for 2013 as in Enseling et al. (2013).

[10] For example, the study by Enseling et al. (2013) assumed that the costs for exchanging the central heating were accounted for maintenance costs, because it would have needed to be replaced anyway.

interest rate r is fixed at 3%. While obviously r has an influence on the EE investment decision (Clinch and Healy 2001; Morrissey et al. 2013), it is not the focus of this analyses.

Cash flows CF_t:	
Current energy consumption F_c	241 kWh/m²a * 163 m² = 39,283 kWh/a
Energy savings ε	5%-80%
Net Present Values NPV_i:	
Investment costs I_0	10,000-60,000€ (baseline: 31,133€)
Time horizon T	10/15/20/25 a
Risk-free interest rate r	3%

Table 2: Parameters for calculation of the CF_t and NPV_i.

In order to derive the objective probability of each of the 10,000 NPVs a Kernel Density Estimator (KDE) is applied to estimate the probability density function.[11] By doing so, we derive all objective probabilities $p(\Delta NPV_i)$. These are the basis for further analyses of the difference between EUT and CPT, for evaluation of EE investments.

IV.1.5.3 CPT and EUT Analysis

The aim of this study is to explain the EE gap by comparing an EE investment decision based on EUT and CPT. We computed the EUT and CPT values for different combinations of input parameters, as described above.[12] For given input parameters, when both theories result in the same algebraic sign, the decision for an EE investment is the same and the EE gap cannot be explained. However, if the result for EUT is positive, and negative for CPT, the methods lead to different decisions. In this case, the EE gap can be explained by decision-making based on perceived values instead of expected utility.

In accordance with CPT, the natural reference-point of the EE investment is ‘0’, because “the reference state usually corresponds to the decision maker’s current position” (Tversky and Kahneman 1991, p.1046). We framed the EE investment decision in such a way that the maintenance measure (i.e., refurbishment of the existing house) would be carried out in any

[11] We applied the KDE with different kernels and bandwidths and achieved very similar results.
[12] As argued earlier, in the comparison we only consider CPT as advancement of original PT to overcome possible violations of first-order stochastic dominance. However, in our analysis, PT and CPT only exhibited minor, negligible deviations. Due to space limitations we do not elaborate on these results.

case. Hence, if no decision about the EE investment were made, no additional costs or benefits would occur. Thus, we set $\Delta NPV_i = NPV_i$ for the following analysis. If the EE investment is carried out, the resulting NPV resembles exactly the gains or losses, as opposed to no additional investment. However, the reference-point "can also be influenced by aspirations, expectations, norms, and social comparison" (Tversky and Kahneman 1991, p. 1046-47). To account for this fact and because of its major influence on the final decision, we discuss the influence of different reference points in Section 5.4.3.

In order to assess the impact of the various elements of CPT on the EE investment decision, we implement the different elements of CPT by means of a systematic approach similar to that used by Babcock (2015) and Dichtl and Drobetz (2011). This modular structure allows us to examine and separate the impact of different elements of CPT on the EE Gap.

(1) First, we just apply the value function in Eq. (2). However, we set the parameter for loss aversion to $\lambda = 1$, and omit the weighting function of Eq. (3).

(2) Second, we use Eq. (2) and set $\lambda = 2.25$. Thus, we also account for loss aversion.

(3) Finally, we account for all the elements of CPT as shown in Eq. (2)–(5).

We compare the results of the CPT analysis with EUT as described in Eq. (1). Thereby, we distinguish two utility functions $u()$ to consider different risk preferences:

(1) A linear utility function, representing a risk-neutral decision-maker: $u(\varphi_i) = \varphi_i$, and

(2) A power utility function that implies Constant Relative Risk Aversion (CRRA):

$$u(\varphi_i) = \begin{cases} \frac{1}{1-\theta} \cdot \left({\varphi_i}^{1-\theta} - 1\right) & for\ \theta \neq 1 \\ ln(\varphi_i) & for\ \theta = 1 \end{cases}, \tag{9}$$

For all levels of wealth $\varphi_i = \varphi_0 + x_i > 0$, where $\theta > 0$ is the degree of relative risk aversion. For EUT, a utility function representing CRRA is applied to calibrate the degree of risk aversion of EUT. CPT exhibits CRRA for outcomes $x_i > 0$. The Arrow-Pratt measure for relative risk aversion[13] shows that, in the positive domain, the value function (i.e., x^α) exhibits a relative-risk-aversion coefficient $\theta = 1 - \alpha$. Because total wealth is relevant for EUT, it is not a drawback that the utility function is only defined for the positive domain. It seems implausible that any negative outcome x_i will exceed initial total wealth φ_o, because in the

[13] The Arrow-Pratt measure for relative risk aversion can easily be calculated by: $-x \cdot u''(x)/u'(x)$.

scenario assumed, the decision-maker is a house-owner, which implies a certain level of wealth.

However, applying a utility function exhibiting CRRA for EUT and CPT does not automatically make them comparable. Kahneman and Tversky (1979) estimated the value of α over modest stakes as well as in dependence of the reference point and the level of loss aversion. Thus, the resulting risk aversion coefficient $\theta = 0.12$ may not be suitable to evaluate total wealth φ_i for EUT. This becomes obvious when comparing $\theta = 0.12$ with other empirical estimates. Often a much higher relative risk aversion coefficient (between '1' and '3') is found. For example, Layard et al. (2008) used a cross-sectional survey of subjective happiness and panel surveys between 1972 and 2005. They found a combined estimate of $\theta = 1.26$, which is more than a tenfold increase in relative risk aversion compared to the value of Kahneman and Tversky. To account for this fact, in the following, we also compute EUT-values based on higher θ-values, while keeping the parameter α for CPT constant (implying a relative risk aversion coefficient of 0.12). We used Eq. (9) instead of x^{θ} because the latter function is restricted to $0 < \theta < 1$ for risk aversion.

IV.1.5.4 Main Simulation Results

The results are based on a comparison of different parameter settings for the energy price simulation by Eq. (8), the NPV calculation by Eq. (6), and of the EUT and CPT calculations. The resulting decisions based on EUT and CPT are compared in a matrix depicting input combinations of investment costs I_0 and energy savings ε. Such a matrix is depicted in Figure 3 for different risk aversion parameters θ. We apply this combination, because I_0 and ε are the most important drivers for relevant decision criteria (Anderson and Newell 2004) and the NPV_i, as well. For example, Hope and Booth (2014) found that high up-front costs are the main reason why landlords do not execute EE investments. Given a fixed set of input parameters for price simulation etc., this setting allows comparison of rational decision-making and decision-making based on perceived values for different combinations of I_0 and ε. For the following analysis, combinations of I_0 ranging from 10,000-60,000€ (in increments of 1,000€) and ε ranging from 5-80% (in increments of 5%) are examined. For every set of combinations of I_0 and ε where EUT is positive but CPT is negative, the EE gap can be shown. *Ceteris paribus*, these are settings where the perceived value of CPT leads to a rejection of the EE investment. However, the analysis and conclusions are restricted to the intervals spanned by the incremental increase of investment costs (by 1,000€) and energy savings (by

5%). Thus, in the worst case, while this analysis might identify an effect in the range 5,000–15,000€ it cannot be excluded that the actual change occurred in the range 4,001–15,999€. For the sake of clarity and computation time, however, we believe that this is an acceptable simplification. In this first attempt, it is not our objective to derive very detailed prices, but rather to demonstrate the general effect. Note, not all combinations must necessarily be technical and economically realistic combinations of investment costs I_0 and achievable energy savings ε. However, for the sake of completeness, and in order not to be reproached for arbitrariness of the chosen range of parameters, all the computed values are depicted.[14]

The analyses emanate from a baseline scenario and subsequently examine the effects of varying input parameters. These include the influence of increased volatility σ of the domestic fuel oil price P_t and the reference point RP. As described in Section 5.3, we apply a modular approach to CPT to examine the influence of different elements of CPT on the final EE investment decision. Moreover, for EUT, we distinguish between risk-neutrality and different levels of risk-aversion. Therefore, first, we introduce the baseline scenario and subsequently examine the influence of different parameters.

[14] However, this comes with the drawback that the effect of the EE gap may seem visually small.

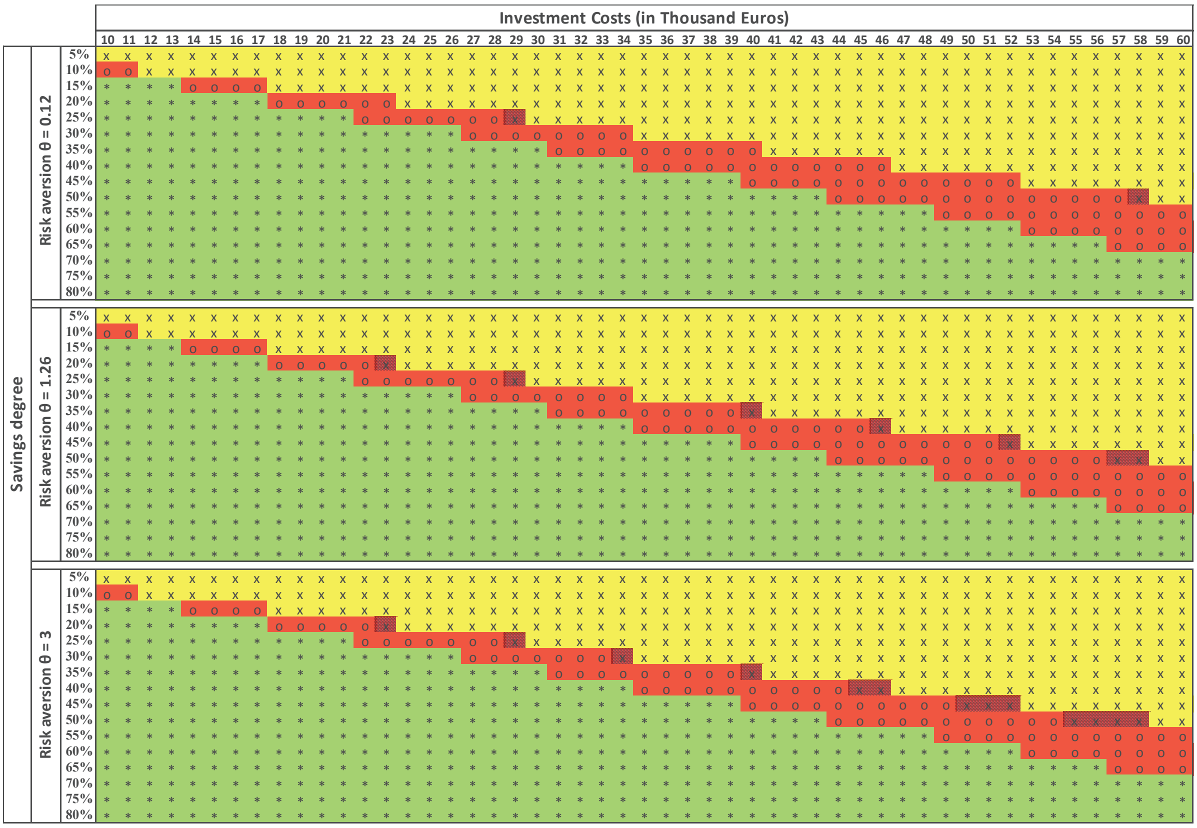

Figure 3: Influence of risk aversion θ on the results as compared to risk-neutrality.

IV.1.5.4.1. Baseline Scenario

Our baseline scenario starts from a risk-neutral EUT decision-maker and assumes a long-term trend of prices $\mu = 4.8\%$, a volatility of energy prices $\sigma = 20\%$, an initial energy price $P_0 = 0.085€/kWh$, an initial wealth $\varphi_0 = 300{,}000€$, and a time horizon $T = 25$ years. The input parameters are used to simulate price paths $i = 1\ to\ 10{,}000$. Then, for every combination of I_o and ε, the corresponding cash flows CF_t are calculated with Eq. (7). The NPV_i are obtained by discounting all CF_t for all $t = 1\ to\ T$ for every price path $i = 1\ to\ 10{,}000$ with Eq. (6). Finally, the resulting distribution is used to calculate the risk-neutral EUT and CPT values. Figure 3 depicts the results for the described baseline scenario, given the input parameters specified above and the chosen combinations of I_0 and ε respectively. Note that for reasons of clarity, we do not depict numerical utility values. Rather, an “x” indicates that neither risk-neutral EUT, nor CPT favor the EE investment. Here, “*” indicates that both methods are positive toward an EE investment. Finally, “o” is a combination of I_0 and ε where EUT is positive, but CPT is negative. Those combinations depict situations where CPT is able to explain the EE gap. The hatched combinations of I_o and ε indicate a change in the EUT decision as compared to the risk-neutral case for the corresponding θ.

First, we analyze the rational risk-neutral EUT decision-maker. This implies all "*" and "o" in Figure 3 are positive decisions toward the EE investment. As argued in Section 5.3, we also accounted for different degrees of risk-aversion by varying the coefficient of relative risk aversion θ of Eq. (9). Figure 3 compares how different levels of risk aversion ($\theta = 0.12; 1.26; 3.0$) influence the extent of the EE gap. For example, for $\theta = 3.0, I_0 = 34{,}000€, and\ \varepsilon = 30\%$, a risk-neutral EUT decision-maker would favor the investment while a risk-averse decision-maker would decline it. However, by comparing the results in Figure 3, it becomes clear that for an initial wealth $\varphi_o = 300{,}000€$ the relative risk aversion factor θ has only minor influence. Decreasing the level of φ_o only has a major impact when $\varphi_o < 50{,}000€$. In our setting, this is rather unrealistic because the decision-maker is the owner of the house under consideration, which in most cases should imply a higher level of initial wealth φ_o.

Based on the value ranges for I_o and ε and all risk-aversions under consideration, all investments yielding an energy saving $\varepsilon < 10\%$ would be declined, while all investments yielding savings of more than 50% would be executed. Interestingly, when comparing two successive saving degrees, it becomes obvious that incremental savings of 5% may not cost more than 5,000–6,000€ additional investment costs, to be accepted in both the risk-neutral and risk-aversion cases. For example, in the risk-neutral case, the last acceptable investment cost I_0, to achieve savings ε of 30% is 34,000€, while it is 40,000€ for 35% savings. A risk-averse decision-maker requires a risk discount, so that the costs for incremental 5% savings must decrease, as compared to risk-neutrality, to make an EE investment attractive. While this generally leads to a downward shift in acceptable investment costs I_0, incremental savings of 5% might not cost more than 5,000–6,000€ additional investment costs for a risk-averse decision-maker.

Next, we look at the CPT decision-maker taking decisions based on perceived values. From this perspective, all "o" and "x" in Fig. 4 depict decisions against the EE investment. First, we analyze the implementation of all elements of CPT according to Eq. (2) – (5) and compare it with that of a risk-neutral EUT decision-maker. Deviations of CPT compared to risk-neutral EUT again are marked with "o". Such deviations can be observed for saving degrees ε between 10% and 65%; thus, the EE gap can be clearly identified. The range of deviating values widens as the degree of saving increases. Thus, the higher the combination of saving degree ε and investment costs I_0 under consideration, the higher the gap in the willingness of EUT and CPT decision-makers to invest. For example, for a saving degree of 45% a risk-neutral EUT decision-maker would be willing to invest up to 52,000€, whereas under CPT, this value would be considerably lower (39,000€). This is another way to describe the barrier of high investment costs as pointed out in Section 2.2. While only looking at the EUT does not allow for any conclusions concerning this issue, comparing these results with those for CPT, highlights that the higher the combination of investment costs and energy savings, the more pronounced the EE gap.

Within the CPT framework, this fact can be explained with the increased number of possible negative NPVs. In spite of higher achievable energy savings ε through higher investment costs I_0, because of the stochasticity of energy prices, it is less likely that accrued present value energy savings would exceed investment costs. With prevailing loss aversion such negative outcomes are valued much higher, and thus result in negative decisions. The influence of loss aversion becomes obvious when implementing only the value function of Eq. (2), while omitting loss aversion ($l = 1$) and probability weighting. Then, the extent to which CPT explains the EE gap is negligible. However, when setting $l = 2.25$, but still omitting probability weighting, deviations from EUT evolve. Yet, adding probability weighting does not considerably change the results. This might be explained by a probability distribution where both extremely high and extremely low NPVs, both with low probability, offset each other. Fig. 4 shows the impact of the different elements of CPT compared to risk-neutral EUT. Finally, we can conclude that CPT can explain the EE gap. Thereby, loss aversion has a major influence, while probability weighting and the value function (with $l = 1$), are rather negligible.

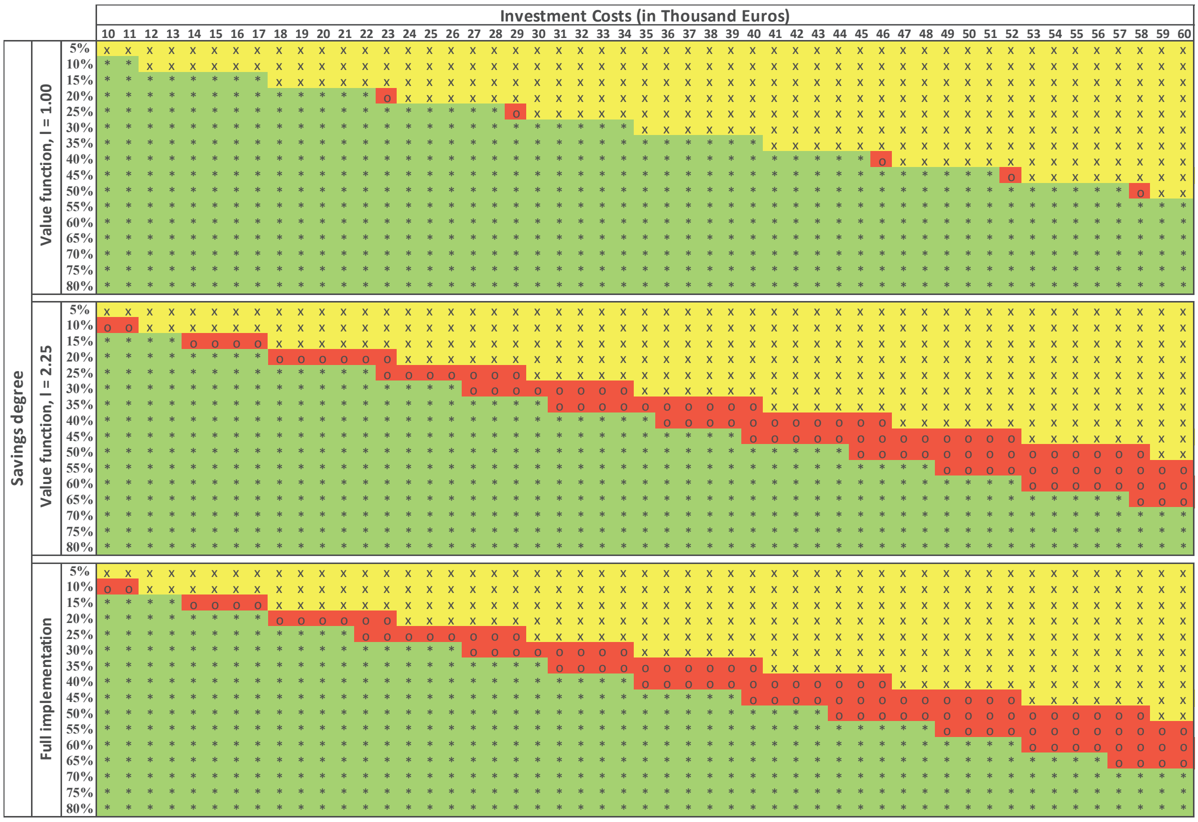

Figure 4: Modular implementation of the CPT.

So far, the comparison is hampered by the fact that a risk-neutral EUT decision-maker does not reflect commonly observed risk-preferences. Risk-neutrality implies that one decides on expected value and that decisions are not affected by the degree of risk in the set of NPVs. However, as we have argued above, the influence of the risk aversion parameter is rather negligible. Only for risk aversion as high as $\theta = 3$, we observe a considerable change in decisions on the EE investment, as indicated by the hatched combinations in Fig. 3. Considering this degree of risk aversion for many saving degrees ε between 20% and 50%, we observe a decreasing number of deviating EUT and CPT decisions, as compared to a risk-neutral EUT decision maker. For example, for $\varepsilon = 45\%$, the range of deviating decisions from 40,000–58,000€ for risk-neutral EUT decreases to the range of 40,000–49,000€ for a risk-averse EUT decision-maker. Thus, one could conclude that the EE gap could be fully explained by simply adjusting the degree of risk aversion. However, when the coefficient of risk aversion θ is increased even more, it leads to unrealistic results. While the EE gap almost vanishes for small investment costs I_0, for higher I_0, even otherwise very profitable combinations of I_0 and ε would not be executed. This might be explained by the theorem of Rabin (2000). The theorem shows that when risk aversion is modeled with a concave utility function in EUT, then even low risk aversion over modest stakes might lead to unrealistic risk aversion over larger stakes. EUT is therefore not very helpful to explain risk attitudes that allow for considerable small-scale risk aversion, and for plausible large-scale risk aversion.

IV.1.5.4.2. Influence of Volatility

One of the most cited reasons for the EE gap is the high risk regarding future energy prices (Diederen et al. 2003; Greene 2011; Hasset and Metcalf 1993). The price path of energy prices is not predictable and, thus, a considerable source of risk for EE investment. High volatility of energy prices also increases the risk of low energy prices and, thus, achievable future savings might decrease. This would result in a higher number of negative NPVs, which are penalized by loss aversion in CPT. So far, the main parameter covering risk, the volatility σ, has been set to $\sigma = 20\%$. In the following, by changing the volatility parameter to $\sigma = 30\%$ and $\sigma = 10\%$, the randomness around the long-term trend μ will be increased or decreased, respectively.

Given a long-term trend $\mu = 4.8\%$, a time horizon $T = 25$, an initial wealth $\varphi_o = 300{,}000€$ and a relative risk aversion $\theta = 0.12$, we analyze the influence of price volatility σ on the extent of the EE gap. Fig. 5 depicts results for all volatilities under consideration in the matrix of investment costs I_0 and energy savings ε introduced earlier. Again, "o" depicts a combination of I_0 and ε where EUT is positive but CPT is negative and, thus, the EE gap can be explained. The results indicate that, with growing volatility, the size of the EE gap increases. For example, for energy savings of $\varepsilon = 45\%$, the EE gap can be explained by CPT for $\sigma = 10\%$ in a range of $7{,}000€$ (I_0 from 46,000–53,000€), for $\sigma = 20\%$ in a range of $12{,}000€$ (I_0 from 40,000–52,000€), and for $\sigma = 30\%$ in a range of $14{,}000€$ (I_0 from 36,000–50,000€). This leads to another observation: with growing σ not only does the size of the EE gap increase, but it also shifts to lower ranges of I_0 for any given ε. On the one hand, this means that with increasing σ the EUT decision-maker would reduce the amount of investment costs I_0 he is willing to pay for a given ε. This effect becomes more pronounced the higher the ε. On the other hand, in a similar way, the CPT decision-maker is also less willing to pay higher I_0 for desired ε. Thereby, this effect is even more pronounced than for the EUT decision-maker. We conclude that rising energy price volatility σ reduces the amount of I_0 the EUT and CPT decision-makers are willing to pay for a given ε. Because this effect is more pronounced for CPT, a higher volatility leads to an increase, and a shift towards lower investment costs, of the EE gap. Thus, uncertainty as the most often stated reason for the EE gap can be explained and quantified using CPT.

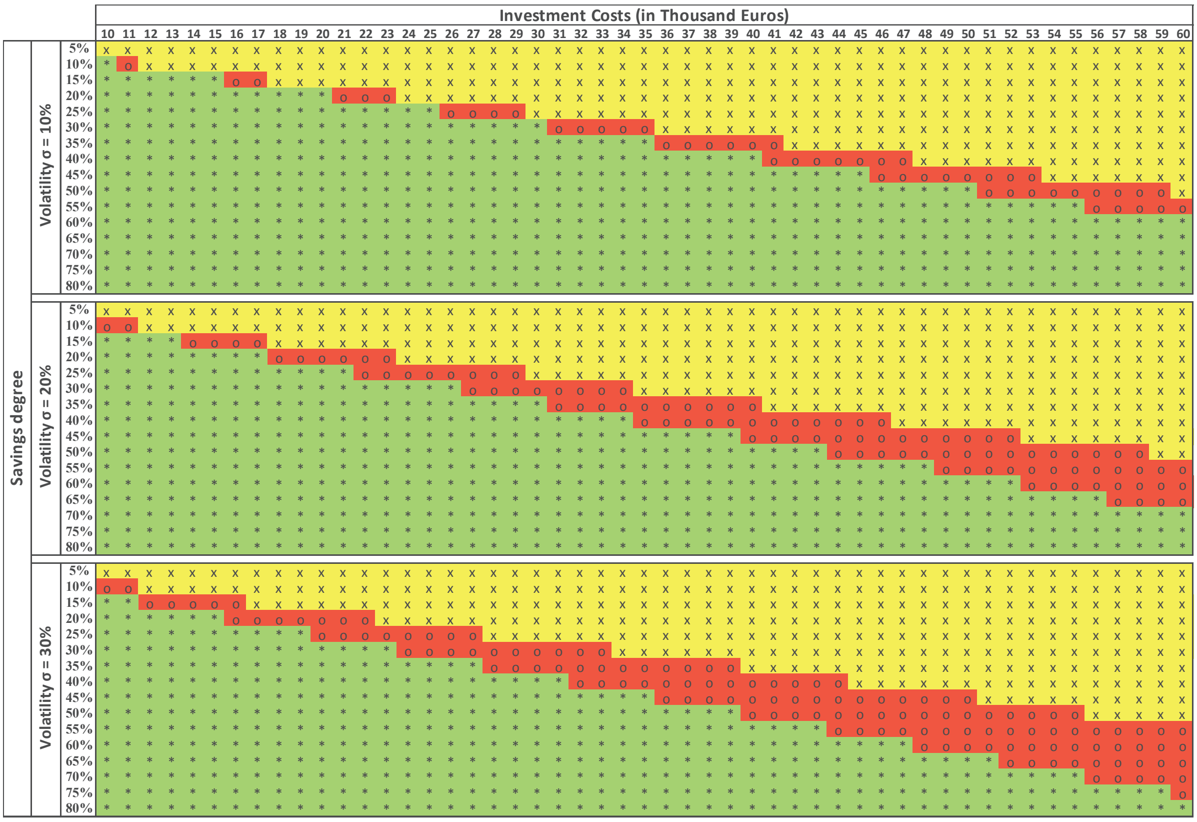

Figure 5: Influence of volatility σ on the extent of the EE gap.

IV.1.5.4.3. Influence of the Reference Point

In Section 5.3, we defined the reference-point $RP = 0$. Thus, $\Delta NPV_i = NPV_i + RP = NPV_i$. It is often unclear how to choose the RP, as Kahneman and Tversky did not focus on a detailed description on how to determine the origin of the value function. Often, as in our case, the reference-point corresponds to the status quo and therefore, $RP = 0$. However, because of the asymmetry of gains and losses divided by the reference-point, its determination has a major influence on choice. Kahneman and Tversky (1979, p.274) stated that "the location of the reference point, and the consequent coding of outcomes as gains or losses, can be affected by the formulation of the offered prospects, and by the expectations of the decision maker". In the following, we analyze situations where gains and losses are not coded relative to the status quo, but relative to expected consumption, expected asset positions, or aspiration levels (Kőszegi and Rabin 2006; Tversky and Kahneman 1991). When the NPV relative to the reference-point RP is defined as $\Delta NPV_i = NPV_i + RP$, then from Eq. (6) it follows that $\Delta NPV_i = -I_0 + \sum_{t=1}^{T} CF_t \cdot (1+r)^{-t} + RP$. Thus, from a computational perspective, a variation of RP corresponds to increasing or decreasing investment costs I_0. When the reference-point is framed as a loss, then $RP < 0$, which results in decreasing I_0. For instance, the decision may be framed in a way that, when not conducting the EE investment, unrealized future energy savings are perceived as a loss. On the other hand, when the reference point is framed as an expected gain, then $RP > 0$, which results in increasing I_0. For example, the decision-maker may expect a minimum return on investment costs of the risk-free interest rate. Then, only returns above that threshold would be perceived as a gain. As change of the reference-point can be shown by adjusting the investment costs I_0, its effects on decision-making can easily be shown in Figure 3. Consider a reference-point $RP = -5{,}000€$ and $\varepsilon = 15\%$, then the former CPT decision for $I_0 = 17{,}000€$ changes to the CPT decision depicted at $I_0 = 17{,}000€ - 5{,}000€ = 12{,}000€$ from not investing in the former, to investing in the latter. Obviously, it is the other way round when $RP > 0$. It follows that when RP is framed as a gain, the EE gap is increased, and it is decreased for a RP framed as a loss. This has already been mentioned for EE and related literature (e.g., Dinner et al. 2011; Goldstein et al. 2008; Gerarden et al. 2015; Hartman et al. 1991), but to the best of our knowledge, we are the first to depict this effect in a quantitative model.

IV.1.6 Conclusion and Policy Implications

Recent environmental policy has included announcements of ambitioustargets in achieving EE in the years ahead. At the same time, it is often asserted that many cost-effective EE investments are not executed. One explanation for this well-known EE gap involves behavioral barriers. In this study, we used CPT, put forward by Tversky and Kahneman (1992), to explain the decision-making of individuals with regards to EE investments. Specifically, we illustrated how the extent of the EE gap is influenced by behavioral biases such as loss aversion, probability weighting, and framing, as compared to the rational decision-maker assumed within EUT. We find compelling evidence for the explanatory power of CPT toward the EE gap and additional valuable insights that may guide the design of effective public policy interventions.

First, our analysis shows that the higher the investment costs, the greater the size of the EE gap. This quantitatively explains the commonly mentioned barrier of high upfront costs. Second, the risk as depicted by the volatility of energy prices also increases the extent of the

EE gap. In line with Rabin (2000), we find evidence that CPT is better able to describe risk-aversion over higher stakes than EUT. Third, by implementing the modular elements of CPT, we can conclude that loss aversion is the major driver of the EE gap. Our results indicate that other elements of CPT such as probability weighting, have a rather negligible influence. As an exception, however, we find the determination of the reference-point to be very important. Depending on how the EE investment decision is framed, or perceived by the decisionmaker, the EE gap might vanish or be amplified. Generally, our results quantitatively back the predictions of related qualitative research about the impact of CPT on the EE gap (e.g., Frederiks et al., 2015; Gillingham and Palmer, 2014; Pollitt and Shaorshadze, 2013; Shogren and Taylor, 2008; Wilson and Dowlatabadi, 2007).

Our results lead us to conclude that CPT provides insights valuable for environmental policymaking. While the standard market failure motivation for government involvement is based on creation of markets, behavioral barriers refer to the individual decision-maker. However, behavioral biases are systematic and pervasive, so we believe government interventions are justified beyond market failure. In otherwise perfect markets, when individuals systematically deviate from optimal decision-making, consumer-focused government intervention may “nudge” individuals toward the right direction without limiting the freedom of choice. This form of intervention has been called libertarian paternalism (see Thaler and Sunstein, 2003).

While the effects of behavioral anomalies on investment decisions in EE have mostly been a “black box” up to now, we provide a first means to explicitly calculate their quantitative impact. Based on a complete implementation of the CPT framework we are able to perform a thorough analysis and quantification of different behavioral biases. In particular, we are able to determine which behavioral biases have the strongest explanation power toward the existence of the EE gap. These results might help to enlighten the “black box” concerning the effects of behavioral anomalies, and therefore, make them effectively correctible by environmental policy measures. Government policies could be based on behavioral insights either by directly addressing the consumer or indirectly by enabling companies to adjust their operations accordingly.

For example, direct policies include targeted and quantitatively backed public awareness campaigns. They can foster EE investments by addressing the most relevant behavioral barriers, such as loss aversion and framing as suggested by Nair et al. (2010). Same holds true for intelligent financial incentives by government programs for EE that directly address behavioral barriers of individual consumers.

On the other hand, indirect policies are mainly related to the support of private companies in order to enable them to offer solutions which address relevant behavioral biases. For example, energy savings insurance, or guarantees, could be promoted to reduce the probability of negative NPVs counteracting loss aversion while presenting an interesting business case for insurance companies (e.g., Mills, 2003). Also, Energy Service Companies may be encouraged to use the CPT framework to align their business model and the pricing of contracts to actual human behavior. Especially energy performance contracting for private consumers could be backed by quantitative insights about human behavior.

Despite these findings, our paper is also associated with some limitations. (1) Our approach relies on several reasonable assumptions about costs and benefits. These influence the cash flow structure and thus, may alter decision-making. Therefore, our analysis could be expanded by adding unobservable costs and benefits, changing the stochastic price process or accounting for the rebound effect. (2) We only focused on behavioral barriers to EE investments implemented in CPT, but neglected possible market failures and other barriers such as time inconsistent preferences. For purposeful policymaking, interrelations between different barriers have to be accounted for and treated in a holistic manner (see Chai and Yeo, 2012). (3) A meaningful comparison of the extent of the EE gap to empirical evidence is hardly feasible within the limits of this paper. For example, most of the evidence on the EE gap is based on implicit discount rates derived on basis of the willingness to pay for an EE investment given future monetary returns. However, our approach is based on utility values that cannot be compared to monetary values in a meaningful way. Further research could focus on this issue. (4) We did not examine the parameters for CPT empirically, but relied on the original specifications by Tversky and Kahneman (1992). However, these parameters could be verified and examined empirically applying randomized controlled trials or quasi-experimental methods in the context of EE investment decisions. (5) Our conclusions were drawn from a realistic but only exemplary application. The introduced approach and its conclusions should be verified by applying it to other scenarios as well.

Despite these limitations, we developed a general and widely applicable approach to evaluate EE investment decisions under CPT. In particular, we showed that behavioral barriers could explain the EE gap. Additionally, CPT provides insights into many of the commonly cited barriers to EE investments. Thus, we created the basis to develop further solutions to quantify behavioral barriers causing the EE gap. By providing insights into the decision-making of an individual EE investor, this paper can support policy makers in creating incentives that accelerate the adoption of EE technologies.

Acknowledgement

Grateful acknowledgement is due to the Ministry of the Environment, Climate Protection and the Energy Sector Baden-Württemberg for their support of the Trafo BW project "c.HANGE (BWT17004)" making this paper possible

IV.1.7 References

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V Results and Future Research

In this chapter, the key findings of the doctoral thesis (Section V.1) and the potential for future research are presented (Section V.2).

V.1 Results

The overarching objective of this doctoral thesis is to contribute to the optimal usage of scarce investment budgets by means of tailored evaluation approaches that consider relevant influencing factors and enable the determination of optimal investment strategies. After motivating the relevance of developing such evaluation approaches, three relevant challenges were addressed in the research papers that are included in this doctoral thesis:

(i) Evaluation of Investments in IT Innovations
(ii) Evaluation of Investments in IT Considering Financial Constraints
(iii) Evaluation of Investments in Energy Efficiency Measures

Regarding the first challenge, the research papers 1 to 3 support an economically reasonable usage of IT innovation budgets by means of providing tailored quantitative approaches that enable to determine and analyze optimal strategies for investments in IT innovations for different investment situations (Chapter II).

Regarding the second challenge, research paper 4 supports the management of long-term IT investment projects by means of a tailored quantitative evaluation approach that combines finance management and the management of IT investment projects and enables the determination of an optimal long-term investment strategy under consideration of financial constraints (Chapter III).

Regarding the third challenge, research paper 5 supports the increase of investments in EE measures by means of a tailored quantitative approach that enables the evaluation of EE investments according to Expected Utility Theory and Cumulative Prospect Theory. This helps to identify possible explanations for the Energy Efficiency Gap and thus, to derive recommendations for policy makers to overcome the Energy Efficiency Gap (Chapter IV).

In the following, the key findings of the research papers of this doctoral thesis are presented. Subsequent, future research opportunities are discussed in Section V.2.

V.1.1 Results of Chapter II: Evaluation of IT Innovation Investments Considering Different Risk and Return Profiles

Chapter II provides support towards economically well-founded investments in IT innovations – by examining three research topics with the help of tailored quantitative evaluation approaches: Firstly, optimal strategies for investments in an emerging IT innovation are determined and analyzed for different possible investment situations (Section II.1). Secondly, to enable the optimal allocation of periodical budgets to IT innovations of different maturity, optimal long-term strategies that dynamically consider the impact of organizational learning are determined and analyzed (Section II.2). Thirdly, ex ante determined optimal dynamic long-term IT innovation investment strategies are analyzed from an ex post evaluation perspective (Section II.3).

- In Section II.1, research paper 1 provides a tailored quantitative evaluation approach that considers relevant influencing factors regarding investments in an emerging IT innovation to determine optimal investment strategies considering the timing of possible investments (Objective II.1). Based on the evaluation approach, the paper identifies and evaluates crucial determinants and causal relationships of different strategies for investments in an emerging IT innovation (Objective II.2). Thereby, a company's available budget and innovativeness as well as the IT innovation's maturity, economic potential, and associated success probabilities are depicted and analyzed regarding their impact on the value of the investment strategies. By means of the tailored quantitative evaluation approach, the research paper supports the decision of companies whether to engage in an emerging IT innovation rather as First Mover, Late Mover, or by means of a mixed investment strategy (Swanson and Ramiller, 2004). Thereby, the paper quantitatively demonstrates that the timing heavily influences the risk and return profiles of investments in an emerging IT innovation. Regarding company-specific influencing factors, it can be shown, that companies with substantial financial funds can compensate possibly lost First Mover advantages with higher investments as late mover to a certain degree. In contrast, companies with scarce financial resources are in a way forced to invest as First Mover as they cannot catch up lost First Mover advantages by higher investments at a later point in time. An interesting result regarding IT innovation-specific factors is, that for rather disruptive IT innovations (i.e., IT innovations with exceptional economic potential, but also very high risks), like smart dust, or brain-computer interfaces, despite their high uncertainty, early investments are rather advantageous compared to late investments. This indicates, that the exceptional economic chances due to First Mover advantages are worth taking the associated high risks of such early investments. Additionally, it can be shown that most of the time a mixed investment strategy is favorable compared to a strict First Mover or Late Mover strategy.

- In Section II.2, to determine optimal dynamic long-term strategies for the allocation of periodical budgets to IT innovations of different maturity considering the impact of organizational learning, research paper 2 develops an appropriate tailored quantitative evaluation approach (Objective II.3). The quantitative consideration of effects of organizational learning over time – i.e., the development of a company's innovativeness depending on engagements in innovative IT – enriches existing approaches and contributes to scientific literature. Additionally, research paper 2 evaluates and analyzes crucial determinants to reveal causal relationships regarding dynamic long-term IT innovation investment strategies (Objective II.4). Thereby, company-specific factors (available investment budget and innovativeness) as well as IT innovation-specific factors (degree of maturity, probability of success, and market impact) are considered and analyzed. As a major result, it can be shown that optimal long-term IT innovation investment strategies should be dynamically adjusted to a company's changed innovativeness that is influenced over time by organizational learning. Moreover, below-average innovative companies should regularly invest in emerging IT innovations to gain knowledge through organizational learning to catch up with competitors. Additionally, it can be shown that the considered planning horizon influences the superiority of an investment strategy as the influence of organizational learning increases with the number of considered periods. Thus, for a planning horizon of ten periods, necessary adjustments of the IT innovation investment strategy due to organizational learning are more substantial than for a planning horizon of only five periods. Last but not least, it can be shown that a company's optimal dynamic long-term IT innovation investment strategy converges when the company has reached the maximal possible innovativeness, as there is no further improvement possible.
- In Section II.3, research paper 3 also provides a tailored quantitative evaluation approach to determine optimal dynamic long-term IT innovation investment strategies

considering organizational learning. However, in contrast to research paper 2, research paper 3 enables the analysis of ex ante determined IT innovation investment strategies from an ex post perspective (Objective II.5). Thus, the work of research paper 2 can be extended substantially and valuable insights regarding the economic performance of determined investment strategies for different possible scenarios can be derived. Additionally, the economic impact of organizational learning on investments in IT innovations of different maturity can be reviewed from an ex post perspective (Objective II.6). As a result, from an ex post perspective, the increase of a company's innovativeness due to organizational learning is beneficial for all analyzed scenarios. That means, that a company's increasing innovativeness enables a higher NPV from the investments in IT innovations. Therefore, a company should aim at continuous improvement of its innovativeness through a steady engagement in IT innovations. However, IT innovation investment strategies of a highly innovative company are also associated with a higher volatility of resulting NPVs, compared to a lower innovative company. Furthermore, research paper 3 demonstrates that for all analyzed scenarios an investment strategy that is dynamically adjusted to a company's changing innovativeness, outperforms IT innovation investment strategies that are constant over time. This applies to companies with different innovativeness, i.e., companies should adjust their IT innovation investment strategies over time to their changing innovativeness.

V.1.2 Results of Chapter III: Evaluation of Investments in IT Considering Financial Constraints

Chapter III focuses on effects of financial constraints on the economic value of IT investment projects by means of a tailored evaluation approach that integrates finance and information management (Section III.1).

- Research paper 4 enables the quantitative consideration of financial constraints within the evaluation and planning of IT investment projects by means of the developed approach (Objective III.1). Thus, it is possible to anticipate possible losses in the value contribution of an IT investment project due to financial constraints. Furthermore, it can be shown, that financial constraints can decrease the value contribution of the IT investment project considerably (Objective III.2). Thereby, it can be shown that the consideration of financial constraints is of upmost importance if there are currently sufficient financial funds available and future financial constraints are rather binding. In this case, by means of a strategic reserve, a company can hedge the value contribution of the IT investment project and gain the highest advantages compared to an evaluation and planning without a consideration of financial constraints. Thus, Section IV.1 provides a first step towards the closer linking of finance and information management to ensure the value contribution of IT investment projects.

V.1.3 Results of Chapter IV: Evaluation of Energy Efficiency Investments Based on Different Theoretical Frameworks

Chapter IV focuses on the comparison of an economic evaluation of EE investments based on different theoretical frameworks to provide possible explanations of the Energy Efficiency Gap as well as fist suggestions to increase investments in EE measures (Section IV.1).

- In Section IV.1, research paper 5 provides a quantitative approach to evaluate investments in EE measures based on Expected Utility Theory and Cumulative Prospect Theory (Objective IV.1). Thus, possible evaluation differences and their influences on associated investment strategies can be demonstrated and quantified. Based on this, relevant underlying factors that lead to these results (indicating possible reasons for the Energy Efficiency Gap) can be identified and analyzed (Objective IV.2). As major results, it can be shown, that high upfront costs and the risk associated with the EE measure (i.e., how a decision-maker perceives the risk) are the main driver of the Energy Efficiency Gap (Rabin, 2000). Thus, with higher volatility of future energy prices (as central source of risk), the decision-maker's willingness to pay for EE measures decreases and the Energy Efficiency Gap rises – even if the EE investment would still be favorable for a "rational" investor. Based on the quantitative evaluation and the performed analysis, research paper 5 enables the derivation of valuable recommendations for policy makers to promote investments in EE measures, and thus helps to overcome the Energy Efficiency Gap. For example, providing energy saving insurances or guarantees are promising measures which simultaneously offer business opportunities, e.g., for insurance companies (Mills 2003).

V.1.4 Conclusion

In summary, the results of the research papers presented in Chapter II, III, and IV of this doctoral thesis contribute to existing literature by providing tailored approaches to evaluate investments and determine strategies for special investment situations: investments in IT innovations, investments in IT considering financial constraints, and EE investments. Thus, this doctoral thesis contributes to the research areas of IT innovation management, IT investment management, and EE management.

V.2 Future Research

In the following, potential prospects for future research are highlighted for each chapter of this doctoral thesis.

V.2.1 Future Research in Chapter II: Evaluation of IT Innovation Investments Considering Different Risk and Return Profiles

Some specific limitations of research paper 1 that provide opportunities for future research regarding investments in an emerging IT innovation are the following:

- The model provides hypotheses regarding relevant causal relationships that influence the economic value of investments in an emerging IT innovation but cannot further analyze the underlying influencing parameter. Hence, studies to investigate these factors (e.g., regarding a company's individual innovator profile), aiming at the development of methods for a sound quantification, would be valuable (Hevner et al., 2004; Wacker, 1998).
- In the provided approach, selected company and IT innovation-specific influencing factors are considered. However, there are probably additional factors that influence the optimal timing of such investments. For example interdependencies with other complementary technologies, or a company's technology-specific knowledge (besides its general innovativeness) may influence the economic value of early or late investments in an emerging IT innovation.

Regarding the optimal allocation of periodical budgets to investments in IT innovations of different maturity considering organizational learning (research paper 2), and the analysis of ex ante determined optimal IT innovation investment strategies from an ex post perspective (research paper 3), prospects for future research are:

- Although the research papers explicitly consider a company's innovativeness and its development over time due to organizational learning, there is no further differentiation regarding further characteristics of the company, e.g., regarding market share or industry sector. However, the optimal investment behavior of different companies may substantially depend on such factors and differ empirically (e.g., Czarnitzki et al., 2011).

- Furthermore, the papers assume an exogenous market with an average investment in IT innovations of different maturity that does not change over time. However, the changing budget allocation of the company may influence the market average – especially if the considered company is the market leader or a big player like Google or Apple. Furthermore, other possible dynamic changes in the market (e.g., the rush in other new technologies) would change the market's average investments.

Additionally, the following aspects arising from all three research papers of Chapter II and offer further possibilities for future research:

- The papers focus on the allocation of budgets to investments in IT innovations, as one step in the context of the management of IT innovations. However, a holistic management of IT innovations requires more activities. For example, in a first step, companies need to determine how much, if any at all, of the available financial resources should be provided for investments in innovative IT. Additionally, during the execution of the IT innovation investments, they have to be managed based on economic principles to ensure the expected value creation. Thus, developing a holistic IT innovation management approach based on economic principles could be a promising aim for future research (e.g., Nagji et al., 2012).
- The provided approaches focus on particular challenges regarding investments in IT innovations: Research paper 1 concentrates on the timing of investments in an emerging IT innovation. Research paper 2 and 3 deal with different aspects regarding the allocation of periodical budgets to IT innovations of different maturity. However, the challenges are not completely independent and thus, should be treated simultaneously. Hence, they should be managed by means of an integrated, portfolio-based approach that enables a simultaneous short- and long-term management of investments in IT innovations.
- Finally yet importantly, the obtained results should be examined empirically by means of real-world data. So far, the approaches are theoretical models that enable first insights regarding investments in IT innovations and causal relationships regarding optimal investment strategies. However, further empirical studies, benchmark analysis, educated guesses, or expert interviews could help to evaluate and adjust the approaches and their parametrization (Hevner et al., 2004; Wacker, 1998).

Taken together, these potential research opportunities provide various starting points for further contributions to economically well-founded investments in IT innovations.

V.2.1 Future Research in Chapter III: Evaluation of Investments in IT Considering Financial Constraints

Possible starting points for future research regarding the evaluation of investments in IT considering financial constraints as shown in research paper 4 are:

- The tailored approach is a first step towards a valuable combination of finance and information management building up on reasonable assumptions. Future work could further detail underlying assumption, e.g., regarding the relation of investment payments and achievable income payments. Thereby, a distinction regarding different types of IT investment projects should be taken into account (e.g., Nagji et al., 2012).
- The paper's approach only considers two points in time. However, IT investment projects may last longer, leading to further dependencies regarding investments in different points in time. In this context, it would be valuable to analyze effects of a longer considered planning horizon, enabling the possibility to allocate investment payments to several points in time. Thereby, causal relationships of more or less binding financial constraints.

Thus, the paper provides potential for further research to enhance the evaluation and planning of IT investment projects considering financial constraints.

V.2.2 Future Research in Chapter IV: Evaluation of Energy Efficiency Investments Based on Different Theoretical Frameworks

The major limitations that provide room for future research regarding the evaluation of investments in EE measures as shown in research paper 5 are:

- The approach of the research paper is built up on reasonable but yet simplifying assumptions about costs and benefits of the EE investment (e.g., possible saving degree or future development of the energy price). In this context, the assumptions could be detailed for example by considering further risks like stochastically changing saving degrees or a stochastic rebound effect reducing desired energy savings. Additionally, the consideration of further unobservable costs and benefits (e.g., an improved indoor climate) may enable further insights regarding investments in EE measures.

- The research paper focuses on analyzing behavioral barriers to EE investments based on Cumulative Prospect Theory. Thereby, possible market failures and other barriers are neglected. However, to enable a derivation of effective policy measures, further possible barriers and their interdependencies should be considered in a holistic manner (Chai and Yeo 2012).
- For the evaluation of the EE investments, the original specifications of Cumulative Prospect Theory's parameters were used (Tversky and Kahneman 1992). Although the used parameter values should be generally applicable, an empirical examination could provide further insights regarding an appropriate parameterization in the special context of EE investments.

Taken together, these potential research opportunities provide several starting points for further contributions towards a better understanding regarding investments in EE measures.

V.2.3 Conclusion

Summing up, the research papers presented in this doctoral thesis contribute to the field of economic investment evaluation. They especially investigate investments in IT innovations, investments in IT considering financial constraints, and investments in EE measures. Although this doctoral thesis certainly can only answer some selected research questions, it contributes to previous work in these areas. As the economic evaluation and determination of sensible investment strategies will be an ongoing challenge for companies, individuals, and policy makers, this doctoral thesis hopefully can provide helpful theoretical and practical insights to the selected topics.

V.3 References

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