Decision Support in IT and Risk - On the Economic Valuation of Strategic Decisions in IT Innovation Management, Credit Portfolio Management, and Hedging

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"It ain't what you don't know that gets you into trouble.
It's what you know for sure that just ain't so."

Samuel Langhorne Clemens
better known as Mark Twain
American Author (1835 - 1910)

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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

This doctoral thesis contains the following research papers:

Research Paper 1 (VHB-JOURQUAL 3: category D):

Lindermeir A (2016) Digitalisierung des Innovationsmanagements - Über Chancen und Herausforderungen von IT-Maßnahmen in Innovation Communities.

In: *HMD - Praxis der Wirtschaftsinformatik, 53(4): 543-554*

Research Paper 2 (VHB-JOURQUAL 3: category B):

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.

To appear in: *SIGMIS The Data Base for Advances in Information Systems, 48(1)*

Research Paper 3 (VHB-JOURQUAL 3: category A):

Häckel B, Isakovic V, Lindermeir A, Moser F (2013) Organizational Learning and the Error of Fixed Strategies in IT Innovation Investment Evaluation.
In: *Proceedings of the 34th International Conference on Information Systems (ICIS), Milan, Italy, December 2013*

Research Paper 4 (VHB-JOURQUAL 3: category B):

Klotz S, Lindermeir A (2015) Multivariate Credit Portfolio Management Using Cluster Analysis.

In: *The Journal of Risk Finance, 16(2): 145-163*

Research Paper 5 (VHB-JOURQUAL 3: category B):

Ebach E, Hertel M, Lindermeir A, Tränkler T (2016) Toward an Optimal Hedging Strategy Considering Earnings Volatility Through Fair Value Accounted Financial Derivatives.

In: *The Journal of Risk Finance, 17(3): 310-327*

I Introduction

The relevance of providing (IT-based) decision support

Although the consequences partially are tremendous, companies and their employees often make wrong decisions based on misjudgments, incomplete information, common sense, gut feeling, or because of unmanageable complexity (Bonczek et al., 2014; Gigerenzer, 2007; Khatri et al., 2000; Sadler-Smith et al., 2004; Swanson et al., 2004). By making these wrong or at least suboptimal decisions, often a huge economical potential benefit or otherwise cost reduction, respectively, is lost (Holsapple et al., 1996; Holsapple et al., 2005; Kremic et al., 2006; Udo et al., 1994). Kodak for example - earlier the very successful market leader of camera systems and photographic films with up to 90% market share - made a fundamentally wrong decision in firstly not producing and selling digital cameras. However, the competitors recognized the trend of digital photography, whereas Kodak misjudged the situation and suffered from the wrong decision. By doing so, the company ended their over 100 years history, their multi-billion dollar revenue collapsed and finally they had to declare bankruptcy in 2012 (Gustin, 2012). Thus, companies should have a strong interest in making the right decisions in order to improve economic efficiency as well as long-term sustainable value creation (Bhandari et al., 2008; Charnes et al., 1978; Holsapple et al., 2005; Power, 2008). However, in order to improve decision quality, companies and their employees need to be supported within decision making.

The reasons for wrong or suboptimal decisions are manifold (Bonczek et al., 2014; Candor et al., 2009; Poch et al., 2009; Schwarz, 2000; Trevino et al., 1990; Walker et al., 2003):

Information availability and processing:
First, companies or employees often do not consider all information and dependencies within their decision making process. Partially, this information is simply not available as it has not been or cannot be collected. Furthermore, the available information partially is simply not considered to be relevant for the decision, but especially the flood of information through information technology (IT) complicates a comprehensive procurement, processing and analysis of information and therefore profound decision making. However, making decisions on incomplete information usually leads to suboptimal decisions and therefore to economical disadvantages.

Behavioral aspects:

Additionally, employees often make decisions based on emotions or gut feeling and do not consider the facts from a rational point of view. Hence, if employees for example show great personal interest for a project, or if their individual goals depend on a decision, they are assumed to make individual decisions that are not necessarily optimal for the company.

Decision complexity:

Moreover, decisions get more and more complex and are partially impossible to understand thoroughly and entirely for a human being. Especially numerous dependencies to other problems, highly interconnected decision problems as well as the flood of information often cannot be fully understood and managed by human decision makers. In the decision making process, for example, often not all alternatives can be compared properly due to complexity. Instead, only a limited set of possibilities is discussed and the optimal solution for the company potentially cannot be identified.

Furthermore, there are other reasons for suboptimal decision making, but all of them usually imply an economic disadvantage for a company in the long term.

In order to improve decision quality and to prevent the outlined reasons for suboptimal decisions, IT-based decision support is often helpful. The IT component thereby - if set up properly - promises the processing of more information, does not behave emotionally or from an individual perspective, and is able to handle highly complex problems. Improving decision making therefore promises substantial economic benefits and long-term sustainable value creation, as decision quality can be improved (Holsapple et al., 1996; Holsapple et al., 2005; Udo et al., 1994). Decision support can have various manifestations (Bonczek et al., 1980; Bonczek et al., 2014; Power, 2008; Power et al., 2015; Shim et al., 2002): The possibilities range from defined decision rules as a guideline for decision makers to completely automated decision making processes.

Nevertheless, the relevance of decision support differs across the various areas of application and even decision problems. Thus, an overview of the relevance of decision support in IT and decision support in risk - as two exemplary but highly relevant areas of application - is given in the following.

The relevance of decision support in IT

Although information technology already conquers almost all sectors and companies for decades, IT gets a more and more decisive factor for business success (Andal-Ancion et al., 2003; Aral et al., 2007; Barua et al., 2001; Haltiwanger et al., 2000; Porter et al., 1985; Ramirez et al., 2010; Schryen, 2013). The rapid technological change forces companies to engage with IT continuously in order to remain competitive, to avoid inefficiency and to fulfil customers' needs for technological progress (Atzori et al., 2010; A.T. Kearney, 2012; Porter et al., 1985; Zhu et al., 2003). At the present time (in the middle of the 2010s), companies need to deal with information technologies like internet of things, big data, virtual reality, cyber physical (production) systems, machine learning, or mobile technology in order to improve long-term economic success (Broy et al., 2012; Chui et al., 2010; Gartner, 2015; Wortmann et al., 2015). The high complexity of these technologies and especially the consolidation between virtual world and real world including the inevitable interdependencies between these two worlds involve a high risk potential, but also promise benefits that, however, are hard to assess. Consequently, companies are faced with a variety of possible IT investment alternatives and complex investment decisions. Furthermore, as investment budgets and resources are limited, economic decisions about the engagement in IT need to be well-founded in order to balance risk and return potentials (Beccalli, 2007; Kohli et al., 2008; Lee et al., 2011; Melville et al., 2004; Schryen, 2013). Thus, as mentioned earlier, employees need to be supported within the usually very complex process of decision making in IT in order to avoid wrong decisions with negative economic impact.

The relevance of decision support in risk

Moreover, the management of risk is getting more and more important for companies in all sectors as ecosystems are becoming more complex and interconnected. Furthermore, in the majority of cases, risk exposures are increasing substantially over time and partially reach unforeseen and business-endangering heights due to less restrictive granting of credits that comes along with loose monetary policy (Begenau et al., 2015; Crotty, 2009; Power, 2009). Consequently, when these risks are not managed accurately, companies can be faced with bankruptcy as the financial crisis in the late 2000s showed impressively (Aebi et al., 2012; Atiya, 2001; Cornett et al., 2011; Saunders et al., 2010). Thus, handling risks is a crucial task for companies to improve economic success in the long term, to ensure stability, and to survive times of crisis. However, companies have different possibilities to handle risk in order to guarantee a sophisticated and promising risk management (Albrecht et al., 2005; Gleißner, 2011; Rolfes, 1999; Romeike, 2008): First, companies can decide not to take a risk if the risk/return ratio does not match with the company's strategic goals. Moreover, if a company took some risks but is not willing to keep them anymore, these risks can be transferred to other market participants that are willing to take them. Furthermore, companies can avoid potential losses through risk controlling measures like hedging. However, all of these and similar approaches demand for a well-founded and precise analysis of risks in order to make the right decisions about their handling and in order to prevent economic disadvantages (Horlick-Jones et al., 2001; Walker et al., 2003). Consequently, the need for a well-founded identification, assessment, controlling, and monitoring of risks demands for decision support in risk management. Otherwise, the company may be faced with huge economic disadvantages.

Particular areas regarding decision support in IT and risk

When making decisions with an economic impact, there are, among many others, three selected, particularly important decision areas regarding providing well-founded decision support in IT and risk that are addressed in this doctoral thesis (Chapters II, III, and IV):

(i) Providing decision support in IT innovation management

(ii) Providing decision support in credit portfolio management

(iii) Providing decision support in hedging

Decision area (i) "Providing decision support in IT innovation management"

Regarding the first decision area: As mentioned above, decision support plays an important role in IT. When integrating new IT in business activities, the successful IT innovation management enables the companies to keep pace with the technological progress, the increasing market expectations and even shorter product lifecycles (Abrahamson et al., 1999; McAfee et al., 2008; Rogers, 2003; Swanson, 1994; Tushman et al., 1986; Van der Panne et al., 2003). Thereby, companies are forced to continuously innovate and consequently renew or expand their products, or otherwise the (more innovative) competitors will gain market shares. In order to avoid these disadvantages, companies necessarily need to make the right decisions in IT innovation management. Within decision making in IT innovation management, especially three aspects are investigated in this doctoral thesis: First, a company needs to decide which information technologies should be used to improve (IT) innovation management projects and processes. The digitalization of collaboration, workflows, networking, and idea generation allow for an increased efficiency in IT innovation management, but, in turn, induce costs. Second, various (investment) alternatives have to be considered in IT innovation management. A company for example definitively needs to decide on whether, when and to which extend to invest in IT innovations with different maturity. On the one hand, fashionable IT innovations (also called emerging IT innovations as they are absolutely new) promise high yield but involve high risk, whereas, on the other hand, mature

IT innovations promise lower risk but also imply lower yield (Swanson, 1994; Swanson et al., 2004). Third, a company needs to consider innovation-specific and company-specific aspects when deciding on the investment in IT innovations. When deciding on allocating limited (investment) resources to IT innovation management projects, a company especially needs to consider its innovativeness - i.e., its ability to innovate - and the fact that this ability can be improved or deteriorated by engaging in IT innovations - also known as organizational learning - in decision making in order to improve decision quality. This challenge is addressed in Chapter II of this doctoral thesis.

Decision area (ii) "Providing decision support in credit portfolio management"

Regarding the second decision area: Similarly important as decision support in IT innovation management is decision support in the field of risk management, as mentioned above. Especially the management of credit risk exposures is a crucial task for companies, as credit exposures increased dramatically over time in most sectors and most countries (Begenau et al., 2015; Crotty, 2009; Power, 2009). In this context, obviously especially financial institutions are affected by these enormous credit risks. As a consequence, the regulatory authorities forced and still force financial institutions to limit their risk exposures in relation to their equity. In order to remain competitive and to maximize the expected return despite the risk limitation, credits with a poor risk/return ratio need to be avoided. At best, these credits are identified before they are closed, but subsequently, they need to be restructured or sold. To determine these credits with a bad risk/return ratio in a financial institution's portfolio and to make the right decisions about restructuring or sale, a well-founded analysis of the credit portfolio from an integrated risk and return perspective is necessary. Furthermore, when the existing credit portfolio was analyzed, rules for the signing of new contracts could be defined in order to improve decision making in credit sales and to optimize the institution's portfolio according to the strategic goals. However, the well-founded analysis of a credit portfolio from a risk and return perspective is a difficult task. Due to the interdependencies, the complexity of the credits and the specific characteristics of each credit contract, credit risk managers need to be supported in decision making in order to increase decision quality and therefore to enhance credit portfolio's risk/return position. This challenge is addressed in Chapter III of this doctoral thesis.

Decision area (iii) "Providing decision support in hedging"

Regarding the third decision area: Furthermore, decision support in the field of hedging is another important decision area - particularly when deciding on hedging financial transactions in order to reduce a company's risk. Thereby, the decision of hedging an existing transaction or the portfolio has to be made wisely, as it usually also decreases the expected return of the existing transaction or the portfolio and induces costs. Consequently, the human decision maker needs to be supported in order to make the optimal decisions considering the portfolio's complexity, the transactions' interdependencies and the regulatory requirements. Within this decision making process, various facts have to be considered simultaneously and balanced in order to determine the economically optimal hedging degree from an integrated risk and return perspective. One fact so far mainly neglected by science and practice, but increasingly important due to fair value accounting, is hedging against earnings volatility. In particular, fair value accounted financial derivatives (as meanwhile intended by IFRS and IAS) usually increase a company's earnings volatility, as they are not accounted with their historical costs but at their current price, which, in turn, fluctuates over time. However, investors usually perceive this variation in earnings volatility as a form of uncertainty or risk. Consequently, earnings volatility has to be considered when deciding on the optimal hedging degree, as the company should consider the investors' interests. This challenge is addressed in Chapter IV of this doctoral thesis.

Structure of the introduction

In summary, the lack of well-founded decision making in research and practice poses challenges in three selected, particularly important decision areas regarding (i) decision support in IT innovation management, (ii) decision support in credit portfolio management, and (iii) decision support in hedging, which are addressed in this doctoral thesis. 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 fields of decision support in IT and risk - especially in IT innovation management, credit portfolio management, and hedging - as prominent topics in research and practice. Table 1 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	**Decision Support in IT Innovation Management (Research Papers 1, 2, and 3)**
Objective II.1:	Determining opportunities as well as challenges for different forms of innovation communities
Objective II.2:	Identifying and evaluating possible digitalization initiatives to improve effectiveness and efficiency of innovation communities
Objective II.3:	Evaluating the crucial determinants in strategic IT innovation investment decisions
Objective II.4:	Developing a mathematical approach to support decisions on the IT innovation investment strategy considering organizational learning
Objective II.5:	Determining causal relationships in IT innovation investment strategy
Objective II.6:	Determining and evaluating the evaluation error from fixed compared to dynamic IT innovation investment strategies
III	**Decision Support in Credit Portfolio Management Considering Risk and Return (Research Paper 4)**
Objective III.1:	Providing a structured approach to analyze credit portfolios from a risk and return perspective using the statistical method ‘cluster analysis’
Objective III.2:	Analyzing and evaluating different credit portfolios of a German financial institution by conducting several cluster analyses

IV	**Decision Support in Corporate Hedging Considering Earnings Volatility (Research Paper 5)**
Objective IV.1:	Developing a novel approach to quantify the cost of capital induced by earnings volatility
Objective IV.2:	Determining the optimal hedging strategy considering the costs of earnings volatility and a profit reduction through hedging activities
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: Decision Support in IT Innovation Management

Research Paper 1: *"Digitalisierung des Innovationsmanagements - Über Chancen und Herausforderungen von IT-Maßnahmen in Innovation Communities"*

Due to short product lifecycles, highly competitive markets and increasing market expectations, innovations are crucial for a company's success (Demirag et al., 1992; Gupta et al., 1990; McAfee et al., 2008; Tushman et al., 1986; Van der Panne et al., 2003). At the beginning of the innovation process, the idea generation phase and idea evaluation phase are essential parts of innovation management (Frishammar et al., 2007). In order to improve innovation management and to survive in highly competitive markets, many companies introduce innovation communities within their innovation management processes (West et al., 2008). These innovation communities - in contrast to traditional innovation management driven by a single research and development department - are characterized by collaborative co-work of several organizational units of a company and sometimes with the integration of a competitor or the (potential) customer in idea generation and idea evaluation (Gaubinger et al., 2009; Gerybadze, 2003). However, different forms of innovation communities like knowledge exchange, open innovation community or internal innovation community show different characteristics and individual advantages and disadvantages (Bansemir et al., 2012; Coakes et al., 2007; Reichwald et al., 2009). Furthermore, the economic success of these innovation communities can be improved by various digitalization initiatives. However, the decision about concrete digitalization initiatives obviously influences the costs of the innovation community substantially. Consequently, the decisions about the introduction of digitalization initiatives in the context of innovation communities have to be made wisely and mindfully instead of only being based on common sense and a gut feeling. In order to improve such decision making processes, research paper 1 addresses the following research questions:

- What are the characteristics, opportunities as well as challenges of different forms of innovation communities?
- Which digitalization initiatives improve effectiveness and efficiency of innovation communities?

- What practical recommendation about the usage of digitalization initiatives can be given for companies with different innovativeness?

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

After having generated and evaluated innovative ideas for new products or new services with the help of an innovation community as shown in research paper 1, the company needs to decide about the investment in and therefore the realization of concrete ideas - for example with regard to concept development, concept evaluation and commercialization (Frishammar et al., 2007). In the context of IT innovations - which show some particularities - a given company-specific innovation budget has to be allocated optimally to different investment alternatives (Abrahamson et al., 1999; McAfee et al., 2008; Rogers, 2003; Swanson, 1994). At first, a company needs to decide on the optimal investment strategy for IT innovations of different maturity (Fenn et al., 2008). On the one hand, emerging IT innovations are expected to have high return potential but also high risk as they are revolutionary but their success is quite uncertain (Fenn et al., 2008; Ravichandran et al., 2011; Rogers, 2003; Wang, 2010). On the other hand, mature IT innovations are expected to have smaller return, but also smaller risk as they already have a wider adaption at the market (Fenn et al., 2008; Wang, 2010). However, the decision about how much budget should be allocated to which investment alternative is only occasionally a well-founded decision (Abrahamson, 1991; Swanson et al., 2004; Wang, 2010). Thus, when deciding on the optimal IT innovation investment strategy, different company- and innovation-specific characteristics have to be considered rationally. Next to the innovation's probability of success and its return potential, especially the company's ability to innovate and organizational learning - i.e., how a company can increase its innovativeness through continuous engagement - have to be considered in decision making. Due to the lack of theoretical approaches to determine the optimal IT innovation investment strategy, this research paper aims to support decision making by proposing a mathematical model and by answering 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**: "Organizational Learning and the Error of Fixed Strategies in IT Innovation Investment Evaluation"*

Research paper 3 likewise proposes a mathematical model for analyzing the optimal investment strategy for IT innovations of different maturity considering organizational learning. However, in contrast to research paper 2, the focus is the economic comparison of a dynamic and a fixed investment strategy. Whereas a fixed investment strategy means that the periodical budget allocation is kept constant over time, a dynamic investment strategy implies a periodical adjustment of the budget allocation (Nagji et al., 2012; Swanson et al., 2004; Ross et al., 2002). In practice, companies tend to keep their investment strategy fixed if the strategy was successful (i.e., profitable), political reasons force the company to do so, or the company is unable to determine an optimal dynamic investment strategy (Häckel et al., 2013; Nagji et al., 2012). Nevertheless, economic advantages could be realized by adjusting the investment strategy to new information regarding the innovation's development, the changing business environment, and the company characteristics - e.g., the innovation's probability of success, the market's average engagement and the company's ability to innovate. Especially organizational learning, i.e., how a company's ability to innovate changes over time by investing in IT innovations, should be considered as it is supposed to substantially influence a company's investment strategy. Thus, when deciding on the optimal investment strategy and aiming to maximize a company's profit, a dynamic budget allocation over time has to be considered. Consequently, this research paper focusses on the analysis of the economic advantage of a dynamic investment strategy by answering the following research questions:

- How does a company's innovativeness affect the engagement in IT innovations with different maturity?
- How does a company's individual innovator profile and a fashionable IT innovation's probability of success affect the potential evaluation error of over- or underinvestments in fashionable IT innovations which results from common fixed strategies widely applied in practice?

I.2.2 Chapter III: Decision Support in Credit Portfolio Management Considering Risk and Return

Research Paper 4: *"Multivariate Credit Portfolio Management Using Cluster Analysis"*

As the financial crisis in the late 2000s and early 2010s showed, the correct and well-founded analysis of credits is an important task for financial institutions as these credits may involve high risk for the creditor, the financial sector and even the world economy. The analysis of an individual credit with regard to its risk and expected return is a complex but scientifically well researched process (Henking et al., 2006). However, the much more important task - especially with all the data available due to regulatory requirements and increased information needs - is the well-founded analysis of a credit portfolio including its interdependencies, internal similarities and structural patterns (Yi et al., 2008). The analysis of a credit portfolio is the basis for decisions about the acquisition of new credits, the resale of existing credits or hedging activities to reduce bulk risk. In practice, common methods for credit portfolio management are logistic regression, decisions trees or support vector machines (Lacerda et al., 1999; Paleologo et al., 2010). However, due to increased computational power, increased data availability and limitations in the commonly used analysis techniques, there is a need for a more profound and detailed analysis of credit portfolios (Izenman, 2008; Walter, 2005; Yi et al., 2008). A highly promising analysis technique, so far mainly used in other disciplines like biology, sociology and marketing, is the statistical method 'cluster analysis' (Ferreira et al., 2009; Hill et al., 2006; Kettenring, 2006; Punj et al., 1983; Saraçli et al., 2013). Thereby, a lot of information about the portfolio structure, the interdependencies and similarities can be gathered without the restrictions known from other credit portfolio analysis techniques (Ferreira et al., 2009; Fraley et al., 2002; Mu et al., 2010; Ward, 1963). The information extracted from all the data subsequently can be used to improve decision quality. Thus, research paper 4 contributes to decision support in credit portfolio management by analyzing the advantages and disadvantages of 'cluster analysis', proposing a structured approach to apply 'cluster analysis' in credit portfolio management, analyzing real-world credit portfolios from a financial institution, and answering the following research questions:

- How can a cluster analysis approach that considers the risk and return measures of the credit contracts improve the performance of a credit portfolio?
- What implications can be drawn for future credit management decision support if the underlying classification of a credit portfolio is known?

I.2.3 Chapter IV: Decision Support in Corporate Hedging Considering Earnings Volatility

Research Paper 5: *"Toward an Optimal Hedging Strategy Considering Earnings Volatility Through Fair Value Accounted Financial Derivatives"*

Another important decision a company - in this context explicitly a financial institution - needs to make, is about the hedging activities regarding its financial activities (Beaver et al., 1970; Hodder et al., 2006). Normally, a financial institution has a targeted risk-return profile it is willing to accept and consequently adjusts its hedging activities in order to comply with these internal requirements. Nevertheless, when deciding on the optimal hedging degree, more than just the targeted internal risk-return profile has to be considered. Earnings volatility, for example, does not directly influence a company's risk-return profile from an internal point of view, but does influence the market's or the investor's assessment of the company and the associated risk (Liu et al., 2002; Ohlson, 1995; Riedl et al., 2011). Whereas high earnings volatility indicates risky business activities, low earnings volatility indicates less risky business activities (Graham et al., 2005; Hodder et al., 2006). Earnings volatility was not that important under historical cost accounting, but especially since the introduction of fair value accounting (as meanwhile intended by IFRS and IAS) the relevance of earnings volatility increased substantially. Suddenly, market value changes of financial assets have to be treated as profit or loss and thus, induce a higher earnings volatility (Barth et al., 1995; Beatty et al., 1996; Duh et al., 2012; Hodder et al., 2006). However, investors perceive this volatility as a form of risk and therefore may avoid these companies. Consequently, in order to fulfill the market's need for a well-balanced risk/return ratio and increase attractiveness for investors, the company should consider earnings volatility when deciding on its hedging activities. As research and practice lack of a well-founded methodology to determine the optimal hedging strategy considering earnings volatility, research paper 5 introduces a mathematical model that optimizes a company's hedging strategy. In this context, the research paper addresses the following research questions:

- What is the tradeoff that arises from the dependency between earnings volatility and a company's cost of capital?
- How can the utility of reduced costs of earnings volatility be quantified?
- What is the optimal hedging strategy considering both the expected return of a derivative transaction and the utility of reduced costs of earnings volatility?

- How does the sensitivity toward earnings volatility (reduction) influence the optimal hedging strategy?

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 decision support in IT innovation management, credit portfolio management, and hedging.

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II Decision Support in IT Innovation Management

The main challenge in IT innovation investment strategy is to identify the most profitable budget allocation to different investment alternatives. In practice, these decisions are often based on gut feeling and not the result of well-founded decision making. Consequently, decision makers and therefore companies often do not take advantage of the maximum economic potential of investments in IT innovations. This motivates the need for decision support in IT innovation investment strategy that considers the return as well as the costs induced by different investment alternatives. Chapter II contributes to decision support in IT innovation investment strategy by providing concrete recommendations as well as determining the optimal dynamic investment strategy.

The first research paper *"Digitalisierung des Innovationsmanagements - Über Chancen und Herausforderungen von IT-Maßnahmen in Innovation Communities"* (Section II.1) analyzes different forms of innovation communities to improve effectiveness and efficiency in innovation management. In this context, the opportunities as well as the challenges are discussed. Moreover, digital technologies for the improvement of innovation communities as well as recommendations about their practical applicability are presented.

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) provides decision support for a company's IT innovation investment strategy by optimizing the allocation of a strategic investment budget to IT innovations of different maturity. Thereby, especially the influence of organizational learning is analyzed.

The third research paper *"Organizational Learning and the Error of Fixed Strategies in IT Innovation Investment Evaluation"* (Section II.3) extends the second research paper and its optimization model and similarly determines an optimal dynamic IT innovation investment strategy considering various factors like organizational learning. However, the main focus is the evaluation of the economic disadvantage by applying a fixed IT innovation investment strategy instead of an optimal dynamic strategy.

II.1 Research Paper 1: "Digitalisierung des Innovationsmanagements - Über Chancen und Herausforderungen von IT-Maßnahmen in Innovation Communities"

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Abstract:

The under the megatrend of digitalization focused application of IT solutions can help to make the innovation processes more effective, cost-efficient and faster. In particular, when using the widespread Innovation Communities there is much room for improvement of the innovation process by digitalization initiatives. Thereby, innovations are the co-work of several departments, divisions, organizations or with the involvement of potential customers rather than the work of a singular research and development department. This article particularly examines the opportunities but also the challenges by applying digitalization initiatives in Innovation Communities. First, the three most important forms Knowledge Exchange, Open Innovation Community and Internal Innovation Community including real-world examples are introduced and analyzed regarding the success factors fit-to-market, new-to-market, time-to-market, and cost-to-market as well as the challenges. Further, selected software products (SharePoint, HYVE IdeaNet App, Yammer, RapidMiner) including their influence on the success factors are presented. Related practical recommendations for companies show how the use of digital technologies in Innovation Communities can lead to better innovations (meaning faster, more cost-effective, more revolutionary and more marketable).The recommendations for the form of the Innovation Community and the most promising digitalization initiatives thereby are differentiated between a highly innovative market leader, an average innovative market participant, and a below-average innovative market entrant.

II.1.1 Relevanz von Innovation Communities und die Notwendigkeit der Digitalisierung

„Unsere Industrie erkennt keine Traditionen an - sie erkennt nur Innovationen an."

Mit diesen Worten untermauerte S. Nadella (CEO von Microsoft) die Relevanz von Innovationen gegenüber dem Festhalten an Bestehendem. Aufgrund des zunehmenden Wettbewerbsdrucks und kürzerer Produktlebenszyklen sind Unternehmen aus allen Branchen dazu gezwungen Innovationen zu entwickeln. Die Relevanz sowie die wirtschaftlichen Möglichkeiten von Innovationen erkennt man bspw. an dem Konzern Tesla Motors, welcher die Elektromobilität vor allem dank der technologischen Innovationen massentauglich gemacht hat und mittlerweile über eine ähnliche Marktkapitalisierung wie Audi oder Renault verfügt. Um sich am Markt etablieren zu können, ist somit ein schnelles, kosteneffizientes und zugleich marktorientiertes Innovationsmanagement erforderlich. Als einzelnes Unternehmen birgt dies jedoch auch ein hohes Risiko, wie man an zahlreichen missglückten Innovationen wie der HD-DVD, dem Transrapid oder Virtual Worlds sehen kann. Um die Kosten sowie das Risiko zu minimieren, greifen Unternehmen seit einigen Jahren immer häufiger auf sog. Innovation Communities zurück. Anstatt die F&E-Leistungen durch eine dafür zuständige Abteilung erbringen zu lassen, werden mehrere Abteilungen und Bereiche, aber oftmals auch externe Forschungseinheiten, Wettbewerber und Kunden, in den Innovationsprozess einbezogen. Durch die Beteiligung mehrerer Partner verspricht man sich qualitativ bessere Innovationen als auch kostengünstigeres und schnelleres Innovieren. Erfolgreiche Beispiele für Innovation Communities sind project i, mit dem BMW den Grundstein für die Elektromobilität des Konzerns gelegt hat oder Lego Ideas mit dem Lego die Kunden in die Gestaltung neuer Produkte einbezieht.

Bei allen Vorteilen ist auch dieses Vorgehen kein Garant für erfolgreiche Innovationen. Neben der nicht zu vermeidenden Unsicherheit bzgl. der Marktakzeptanz, können Implementierung und Betrieb sehr kostenintensiv werden. Darüber hinaus sind damit Herausforderungen verbunden, mit welchen sich ein Unternehmen mit einer klassischen F&E-Abteilung nicht konfrontiert sieht: Bspw. dem Risiko des Wissensabflusses an Wettbewerber oder dem steigenden Koordinationsaufwand aufgrund mehrerer beteiligter Organisationen, durch welchen die kollaborative Zusammenarbeit erschwert und kostenintensiver wird. Die Digitalisierung der Prozesse in einer Innovation Community, in Form eines zielgerichteten

Einsatzes von informationstechnischen Lösungen, hilft die Erfolgschancen sowie die Wirtschaftlichkeit zu erhöhen. Die bisher bestehende Literatur konzentriert sich dabei stark auf Charakteristika von Innovation Communities bzw. auf Digitalisierungsmaßnahmen ohne Anwendungsbezug zum Innovationsmanagement. Vor diesem Hintergrund besteht das Ziel dieses Artikels darin, Chancen und Herausforderungen von Innovation Communities herauszuarbeiten, Digitalisierungsmaßnahmen zur Verbesserung des Innovationsmanagements vorzustellen und praxisnahe Handlungsempfehlungen über deren Verwendung abzuleiten.

II.1.2 Wesentliche Ausprägungsformen von Innovation Communities

Gerybadze (2003) definiert Innovation Communities als „Gemeinschaften von gleich gesinnten Akteuren, oft aus mehreren Unternehmen und verschiedenen Institutionen, die sich aufgabenbezogen zusammenfinden und ein bestimmtes Innovationsvorhaben vorantreiben“. Der wesentliche Unterschied zu klassischer Innovation durch eine F&E-Abteilung ist also die kollaborative Zusammenarbeit. Aufgrund der heterogenen Sichtweisen verspricht man sich bessere Chancen auf wirtschaftlich erfolgreiche Innovationen. Da sich in den letzten Jahren in der Praxis unterschiedliche Formen etabliert haben, wird im Folgenden auf die drei wesentlichen Ausprägungsformen sowie deren Charakteristika eingegangen. Eine Übersicht kann Tabelle 1 entnommen werden.

II.1.2.1 Knowledge Exchange

Knowledge Exchange dient laut Coakes und Smith (2007) primär nicht der Entwicklung einer Innovation in Form eines konkreten Produktes, sondern dem grundlegenden Wissensaustausch. Somit können Unternehmen durch Einbindung von Wettbewerbern, Zulieferern, Abnehmern aber insbesondere durch zielgerichteten Austausch mit Forschungseinrichtungen ihr Wissen sukzessive ausbauen und somit die Grundlage für erfolgreiche Innovationen schaffen. Thematisch sind die beteiligten Partner dabei i.d.R. nicht auf einzelne Produkte fokussiert, sondern versuchen ein möglichst breites Spektrum innerhalb der Unternehmensstrategie abzudecken. Als Beispiel für Knowledge Exchange kann die zwischen der Audi AG und der Universität der Bundeswehr vereinbarte Zusammenarbeit genannt werden, welche die gemeinsame Forschung zu elektrischen Antriebstechniken zum Ziel hat (BEM 2016).

II.1.2.2 Open Innovation Communities

Open Innovation Communities haben hingegen das Ziel ein konkretes Produkt zu entwickeln. Auch hierbei sind Wettbewerber, Forschungseinrichtungen und andere Unternehmen der Wertschöpfungskette involviert. Die Besonderheit liegt in der Einbeziehung der Kunden in den Innovationsprozess, um auch deren Bedürfnisse und Ideen frühzeitig bei der Gestaltung neuer Produkte zu berücksichtigen (Chesbrough et al. 2006). Exemplarisch kann dabei die Plattform Lego Ideas genannt werden, auf der Kunden Vorschläge für neue Produkte einreichen können. Bei positivem Feedback werden diese Ideen bis zur Marktreife weiterentwickelt und zum Verkauf gebracht (Lego 2016).

II.1.2.3 Internal Innovation Communities

Internal Innovation Communities zeichnen sich laut Bansemir et al. (2012) primär durch die Beschränkung auf ein einzelnes Unternehmen aus. Anders als üblich, werden jedoch bewusst verschiedene Teams, Abteilungen, Bereiche und sogar Standorte in den Prozess involviert. Thematisch konzentriert man sich bei Internal Innovation Communities ebenso auf die Entwicklung von konkreten Produkten. Das von BMW initiierte project i bspw. war analog zu einer Internal Innovation Community gestaltet und hatte zum Ziel konkrete Elektro- bzw. Hybrid-Automobile zu entwickeln.

Tab. 1 Wesentliche Charakteristika von Innovation Communities

<table>
<tr><th></th><th>Knowledge Exchange</th><th>Open Innovation Communities</th><th>Internal Innovation Communities</th></tr>
<tr><td>Primäres Ziel</td><td>Grundlegender Wissensaustausch</td><td colspan="2">Ideengenerierung und Ideenevaluation</td></tr>
<tr><td>Thematischer Fokus</td><td>Keine Begrenzung innerhalb des Unternehmensfokus</td><td colspan="2">Ein bis mehrere spezifische Themen im Unternehmensfokus</td></tr>
<tr><td rowspan="2">Beteiligte Organisationen</td><td colspan="2">- Ein bis mehrere Unternehmen
- Forschungseinrichtungen
- Wettbewerber</td><td rowspan="2">Ein Unternehmen</td></tr>
<tr><td></td><td>Kunden</td></tr>
</table>

II.1.3 Chancen des Einsatzes von Innovation Communities

Reichwald und Piller (2009) unterscheiden nach vier Erfolgsfaktoren. Die beiden Faktoren Fit-to-Market und New-to-Market bewerten die Innovation im Hinblick auf die Erfüllung der Marktbedürfnisse. Indes bewerten die beiden Faktoren Time-to-Market und Cost-to-Market die operative Ausgestaltung des Innovationsmanagements selbst, also wie effizient die Innovation entwickelt wurde. Im Folgenden werden diese Erfolgsfaktoren genauer beleuchtet und zusammenfassend in Tabelle 2 dargestellt.

II.1.3.1 Fit-to-Market

Mit Fit-to-Market wird die Akzeptanz durch den Markt bezeichnet, d.h. wie stark die Kundenbedürfnisse erfüllt werden. Ein Produkt mit einem besonders hohen Fit-to-Market war bspw. das iPhone, welches zwar technisch nicht revolutionär war, jedoch die Kundenbedürfnisse exakt getroffen hatte. Durch Einbindung mehrerer Perspektiven erhöht sich der erwartete Fit-to-Market, da die Marktbedürfnisse besser eingeschätzt werden können. Insbesondere bei Open Innovation Communities ist mit einem sehr hohen Fit-to-Market zu rechnen, da die Bedürfnisse der Kunden explizit in den Gestaltungsprozess eingebracht werden. Knowledge Exchange ist die Form mit dem geringsten Fit-to-Market, da die Zielsetzung nicht die Entwicklung von konkreten Produkten ist.

II.1.3.2 New-to-Market

Ebenso wichtig ist der Neuigkeitsgrad des Produktes. Neuartige Produkte erregen dabei die Aufmerksamkeit des Marktes und haben die Chance durch ein oder mehrere Alleinstellungsmerkmale große Marktanteile zu gewinnen. Als Beispiel für ein besonders neuartiges Produkt kann Google Glass erwähnt werden, welches eine neue Produktkategorie im Bereich Augmented Reality eröffnete. Analog zu Fit-to-Market ist auch bei Knowledge Exchange der Faktor New-to-Market i.d.R. am geringsten, da die Produktentwicklung nicht im Fokus steht. Bei Open und Internal Innovation Communities ist dieser Faktor sicherlich höher aufgrund der Vielzahl der beteiligten Akteure.

II.1.3.3 Time-to-Market

Für den wirtschaftlichen Erfolg einer Innovation ist indirekt allerdings auch die Effizienz des Innovationsprozesses entscheidend. Je schneller eine Innovation marktreif ist, desto größer ist der Vorteil gegenüber Wettbewerbern. Das Online-Portal Ainbnb schaffte es bspw. in kürzester Zeit mit innovativen Dienstleistungen zur Marktreife sowie durch sukzessive Weiterentwicklungen zu großem Erfolg. Die i.d.R. kürzeste Time-to-Market verspricht die Internal Innovation Community, da etablierte Kommunikationswege genutzt werden können. Bei Open Innovation Communities ist dies aufgrund der Einbindung von externen Partnern deutlich schwieriger. Dennoch ist auch hier bei entsprechender Gestaltung mit digitalen Technologien mit kürzeren Entwicklungszeiten zu rechnen als bei klassischen Innovationsprojekten.

II.1.3.4 Cost-to-Market

Im Fokus stehen auch die Implementierungs- und Koordinationskosten. Erstere ergeben sich v.a. durch das Aufsetzen einer bedarfsgerechten Kommunikationsinfrastruktur. Die Koordinationskosten hingegen ergeben sich durch Personalkosten aufgrund des erhöhten Abstimmungsaufwandes. Die für eine Innovation erforderlichen Kosten können dabei unterschiedlich hoch ausfallen. Während technische Innovationen, wie bspw. die Entwicklung des Airbus A380 mit ca. 12 Mrd. Dollar, i.d.R. sehr kostenintensiv sind, weisen Software-Innovationen, wie bspw. die Entwicklung der Uber-App, deutlich geringere Kosten auf. Die i.d.R. geringsten Kosten weißt Knowledge Exchange auf, da die Zusammenarbeit lose erfolgt und nicht viele Organisationseinheiten eingebunden sind. Bei Open Innovation Communities verursacht die Einbeziehung von externen Teilnehmern i.d.R. die höchsten Kosten.

Tab. 2 Erfolgsfaktoren unterschiedlicher Formen von Innovation Communities

	Knowledge Exchange	Open Innovation Communities	Internal Innovation Communities
Fit-to-Market	Gering	Sehr hoch	Hoch
New-to-Market	Gering	Hoch	Hoch
Time-to-Market	Lang	Kurz	Sehr kurz
Cost-to-Market	Geringe Implementierungs- und Koordinationskosten	Sehr hohe Implementierungs- und Koordinationskosten	Geringe Implementierungs- und mittlere Koordinationskosten

II.1.4 Herausforderungen des Einsatzes von Innovation Communities

Mit der Einführung kollaborativer Zusammenarbeit ergeben sich jedoch auch teilweise erhebliche Herausforderungen, deren Betrachtung für vollumfängliche Entscheidungen zwingend erforderlich ist. Ein Überblick kann Tabelle 3 entnommen werden.

Bei Knowledge Exchange besteht eine Kernherausforderung darin, das aufgebaute Wissen in den Innovationsprozesses einzubeziehen. Bezieht man das neue Wissen nicht in den Innovationsprozess ein, bleibt der Vorteil der Innovation Community ungenutzt. Des Weiteren besteht durch die Einbindung von Externen die Gefahr, dass mehr Wissen abfließt als dazugewonnen wird, was damit den Markt stärkt und das eigene Unternehmen schwächt.

Für die Open Innovation Community ist der Wissensabfluss ebenso eine Herausforderung, da auch hier externe Organisationen eingebunden werden. Darüber hinaus müssen die zu entwickelnden Produkte i.d.R. mit den anderen Teilnehmern der Innovation Community geteilt werden und somit können nur geringere Marktanteile gewonnen werden. Es empfiehlt sich daher bereits zu Beginn der Zusammenarbeit die Nutzungs- und Verwertungsrechte an den Ergebnissen festzulegen, um spätere Unklarheiten und Rechtsstreitigkeiten zu vermeiden. Als weitere Herausforderung existiert aber auch die Gefahr des Scheiterns. Einerseits kann sowohl das Innovationsprojekt selbst scheitern und bspw. keine Ergebnisse generieren, andererseits können sich die Ergebnisse bspw. als marktuntauglich herausstellen oder die Bedürfnisse der Kunden nicht treffen (Bauer 2006). Selbst eine optimal gestaltete Innovation Community mit den klügsten Köpfen, einer passenden Kommunikationsinfrastruktur und den notwendigen Erfahrungen kann keine erfolgreiche Innovation garantieren. Während die meisten Firmen mit intern gescheiterte Innovationsprojekt oftmals nicht an die Öffentlichkeit treten, ist die Liste der am Markt gescheiterten Innovationen sehr lang: exemplarisch sind DVB-H (Rundfunkübertragung für mobile Geräte), Cargolifter (Lastentransport mit Luftschiffen) sowie Google Wave (Online-Kommunikations-Dienst) zu nennen.

Die Gefahr des Scheiterns gilt dabei ebenso für Internal Innovation Communities. Die deutlich größere Herausforderung ergibt sich aber durch ‚Betriebsblindheit', da lediglich ein Unternehmen beteiligt ist. Es fehlt an externen und unvoreingenommenen Perspektiven, welche außerhalb der gewohnten Muster denken. Durch die eingeschränkte Sichtweise verringert sich die Chance einer erfolgreichen Innovation, auch wenn dieses durch die Einbindung einiger Abteilungen, Bereiche und Standorte reduziert werden kann.

Tab. 3 Herausforderungen unterschiedlicher Formen von Innovation Communities

	Knowledge Exchange	Open Innovation Communities	Internal Innovation Communities
Herausfor-derungen	- Wissensabfluss durch Einbindung von Externen - Fehlende Umsetzung aufgrund der losen Zusammenarbeit	- Ggf. Beteiligung von Wettbewerbern an den Gewinnen - Scheitern der Produkt-entwicklung - Wissensabfluss durch Einbindung von Externen	- Betriebsblindheit verhindert uneingeschränktes Denken - Scheitern der Produkt-entwicklung

II.1.5 Mögliche Digitalisierungsmaßnahmen zur Verbesserung des Innovationsmanagements

Einige Herausforderungen von Innovation Communities muss ein Unternehmen eingehen, wenn es auch die damit verbunden Potentiale heben möchte. Zwei wesentliche Hindernisse bei der kollaborativen Zusammenarbeit sind dabei die komplexe Kommunikation sowie die gemeinsame Datenverwaltung, welche sich jedoch durch geeignete Kontrollmechanismen gezielt überwachen und steuern lassen. Der Erfolg für das Unternehmen ergibt sich jedoch v.a. durch Verbesserung der genannten Erfolgsfaktoren.

II.1.5.1 Kollaborationssoftware zur einfacheren Zusammenarbeit - SharePoint

Einen möglichen Ansatz bietet das von Microsoft betriebene SharePoint. Durch die vorgesehenen Team-Webseiten, Newsfeeds, Blogs oder Diskussionsseiten wird die wichtige bereichs- und unternehmensübergreifende Kommunikation vereinfacht und intensiviert. Die grundlegend verankerte gemeinsame Datenverwaltung vereinfacht darüber hinaus den Austausch von Dokumenten und Daten und ersetzt mail-basierte oder redundante Datenhaltung in unternehmensspezifischen Systemen. Ferner ist auch die Aktualität und Konsistenz der Daten garantiert, da zeitgleich an Dokumenten gearbeitet werden kann. Durch den Einsatz von SharePoint können somit durch effizientere Kommunikation und Datenverwaltung die beiden Erfolgsfaktoren Time-to-Market sowie Cost-to-Market verbessert werden. (Drews et al. 2015; Microsoft 2016a; Newell et al. 2009)

II.1.5.2 Mobile Working zur einfacheren und schnelleren Interaktion - HYVE IdeaNet App

Eine weitere Möglichkeit ergibt sich durch den Einsatz mobiler Technologien. Der Einsatz mobiler Hardware in Verbindung mit entsprechender Software verbessert Time-to-Market und Cost-to-Market. Eine Möglichkeit stellt die HYVE IdeaNet App dar, welche explizit für das mobile Arbeiten in Innovation Communities angeboten wird. Einerseits kann man mit dieser App jederzeit und auch unterwegs Ideen in die Innovation Community einbringen. Andererseits ist es möglich schnell Feedback zu geben, wodurch sich die Entwicklungszeit verkürzt. Auch die Kosten reduzieren sich, da eine effizientere und schnellere Kommunikation ermöglicht wird. Die direkten Kosten für die Einführung sind gering, da bestehende Dienstgeräte oder private Geräte genutzt werden können. (Andriessen 2012; Bullinger et al. 2004; HYVE 2016)

II.1.5.3 Soziale Medien zur Intensivierung der Kommunikation - Yammer

Um auch die Erfolgsfaktoren Fit-to-Market sowie New-to-Market zu verbessern, bietet sich der Einsatz von Sozialen Medien an, da unter Einbeziehung von vielen Perspektiven - insbesondere der Kunden - die Marktbedürfnisse besser eingeschätzt werden können. Ein Beispiel hierfür ist das von Microsoft angebotene Yammer, welches die unternehmensweite aber auch unternehmensübergreifende Gruppierung von Mitarbeitern und Kunden ermöglicht. Hierbei stehen im Gegensatz zu anderen Sozialen Medien wie Facebook oder Google+ allerdings nicht der Austausch von privaten Informationen im Vordergrund, sondern die inhaltliche Zusammenarbeit sowie der gegenseitige fachliche Austausch. Dies schafft somit die idealen Voraussetzungen für eine schnelle Vernetzung der beteiligten Personen. Schlussendlich verbessern Soziale Medien auch die beiden Erfolgsfaktoren Time-to-Market sowie Cost-to-Market, da auch hierdurch eine effizientere Kommunikation ermöglicht werden kann. (Lestari 2016; Microsoft 2016b)

II.1.5.4 Big Data & Predictive Analytics zur Informationsgewinnung - RapidMiner

Eine weitere Möglichkeit ein besseres Verständnis der Kundenbedürfnisse zu erlangen, ist die systematische Nutzung der vorliegenden Daten. Klassischerweise können Kundendaten oder Marktanalysen herangezogen werden. Aber es können bspw. auch Daten über die individuellen Kundenbedürfnisse und -anforderungen ausgewertet werden, welche Kunden in Massen öffentlich auf Sozialen Medien wie Facebook oder Twitter zur Verfügung stellen. Unter den Schlagworten Big Data sowie Predictive Analytics verbergen sich schließlich

Methoden, die aus den vorliegenden Daten die relevanten Informationen gewinnen. Anstatt sich auf Intuition zu verlassen, kann das (teil-)automatisiert und objektiviert werden. RapidMiner bspw. ermöglicht die Informationsextraktion durch maschinelle Datenauswertung und -visualisierung. Durch das damit geschaffene bessere Verständnis der Kundenbedürfnisse können die Erfolgsfaktoren Fit-to-Market und New-to-Market verbessert werden. (RapidMiner 2016; Zhang et al. 2013)

Tab. 4 Verbesserung der Erfolgsfaktoren durch unterschiedliche Digitalisierungsmaßnahmen

<table>
<tr><th></th><th>Kollaborations-software</th><th>Mobile (Net-)Working</th><th>Soziale Medien</th><th>Big Data & Predictive Analytics</th></tr>
<tr><td>Fit-to-Market</td><td colspan="2" rowspan="2">Kein nennenswerter Einfluss feststellbar</td><td>Erhöhung des Fits durch Einbindung, Befragung und Austausch mit einer Vielzahl an Personen</td><td>Erhöhung des Fits durch daten-getriebene Analyse der Markt-bedürfnisse</td></tr>
<tr><td>New-to-Market</td><td>Erhöhung des Neuigkeitsgrades durch Einbindung zahlreicher Perspektiven</td><td>Erhöhung des Neuigkeitsgrades durch daten-getriebene Entwicklung neuer Geschäftsmodelle</td></tr>
<tr><td>Time-to-Market</td><td>Verringerung der Entwicklungszeit durch einfachere, persönlichere und engere Kommunikation</td><td>Verringerung der Entwicklungszeit durch effizientere, mobile und permanent ermöglichte Zusammenarbeit</td><td>Verringerung der Entwicklungszeit durch schnellere Kommunikation und effizientere Koordination</td><td rowspan="2">Kein nennenswerter Einfluss feststellbar</td></tr>
<tr><td>Cost-to-Market</td><td>Verringerung der Kosten durch effizientere Schnittstellen, einfachere Kommunikation und direkten Informations-austausch</td><td>Verringerung der Kosten durch einfachere Zusammenarbeit und Nutzung bestehender Infrastruktur</td><td>Verringerung der Kosten durch schnellere Kommunikation und effizientere Koordination</td></tr>
</table>

II.1.6 Praxisrelevante Handlungsempfehlungen

Die vorgestellten Digitalisierungsmaßnahmen tragen zu einer Verbesserung von Innovation Communities bei, jedoch sind diese ebenfalls mit Implementierung- bzw. Betriebskosten verbunden. Es muss folglich ökonomisch fundiert über die Innovation Community sowie die zu implementierenden Digitalisierungsmaßnahmen entschieden werden. Maßgeblich kann dabei der Innovationsgrad eines Unternehmens sein:

Hochinnovative Marktführer sollten nicht das Risiko eingehen, ihre Marktposition durch Wissensabfluss zu gefährden. Es empfiehlt sich folglich der Einsatz von Internal Innovation Communities, da keine externen Teilnehmer eingebunden sind. Als Digitalisierungsmaßnahme eignet sich der Einsatz von Big Data & Predictive Analytics Tools, um die zur Verfügung stehenden Informationen (in selbst generierten, öffentlich zugänglichen oder käuflich erwerblichen Daten) besser nutzen zu können. Der Einsatz von zusätzlicher Kollaborationssoftware und Mobile Working ist aufgrund der bestehenden Infrastruktur nicht sehr hilfreich. Ebenso kann, aufgrund der fehlenden Notwendigkeit Kunden stärker einzubeziehen als bisher, auf Soziale Medien verzichtet werden.

Ein durchschnittlich innovatives Unternehmen hingegen besitzt i.d.R. nicht genug internes Wissen um durch alleiniges Innovieren substantielle Marktanteile zu gewinnen. Folglich bieten sich Open Innovation Communities an, mit welchen externes Wissen gewonnen und die Kundenbedürfnisse besser eingeschätzt werden können. Insbesondere durch den Einsatz von Sozialen Medien kann dieses Ziel besser erreicht werden. Des Weiteren erleichtert Mobile Working die unternehmensübergreifende Kommunikation und Interaktion.

Möchte ein wenig innovatives Unternehmen den Markteintritt wagen, empfiehlt sich der Einsatz von Knowledge Exchange, da zunächst Wissen übertragen bzw. aufgebaut werden muss, bevor an konkreten Produkten gearbeitet werden kann. Da hierbei die Kundenbedürfnisse nicht im Vordergrund stehen, gilt es, sich auf eine möglichst effiziente Kommunikation sowie einen kollaborativen Wissensaustausch zu fokussieren. Dies ist v.a. durch den gezielten Einsatz einer geeigneten Kollaborationssoftware möglich.

Tab. 5 Handlungsempfehlungen für Unternehmen

	Innovation Community	Digitalisierungsmaßnahme
Hochinnovativer Marktführer	*Internal Innovation Community*	*Big Data & Predictive Analytics*
Durchschnittlich innovativer Marktteilnehmer	*Open Innovation Community*	*Soziale Medien* und *Mobile Working*
Wenig innovativer Markteinsteiger	*Knowledge Exchange*	*Kollaborationssoftware*

II.1.7 Ausblick für Wissenschaft und Praxis

Die dargestellten Handlungsempfehlungen zum zielgerichteten Einsatz von Digitalisierungsmaßnahmen stellen einen generischen Rahmen für Wissenschaft und Praxis dar. Sicherlich gilt es im Einzelfall unter Berücksichtigung aller Rahmenbedingungen darüber zu entscheiden, welche Innovation Community und welche Maßnahmen zum Einsatz kommen sollen. Insofern existieren zahlreich weitere Anknüpfungspunkte: Bspw. gilt es weitere Digitalisierungsmaßnahmen zu analysieren und deren Mehrwert zu identifizieren. Darüber hinaus sollten sämtliche Alternativen unter Ertrags-Risiko-integrierter Sichtweise ökonomisch bewertet werden, um fundiert über deren Nutzung entscheiden zu können. Des Weiteren sind auch einige Fragen zur konkreten Ausgestaltung von Innovation Communites noch ungeklärt: Bspw. welche Organisationen bzw. Kunden beteiligt werden sollen, welche fachlichen aber auch kulturellen Anforderungen an die Mitarbeiter gestellt werden müssen oder welche Organisationsstrukturen es zu schaffen gilt. Nichtsdestotrotz sollten sich Unternehmen wegen der genannten Chancen intensiv mit Innovation Communities auseinandersetzen und diese ggf. zumindest parallel zum klassischen Innovationsmanagement einsetzen.

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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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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.

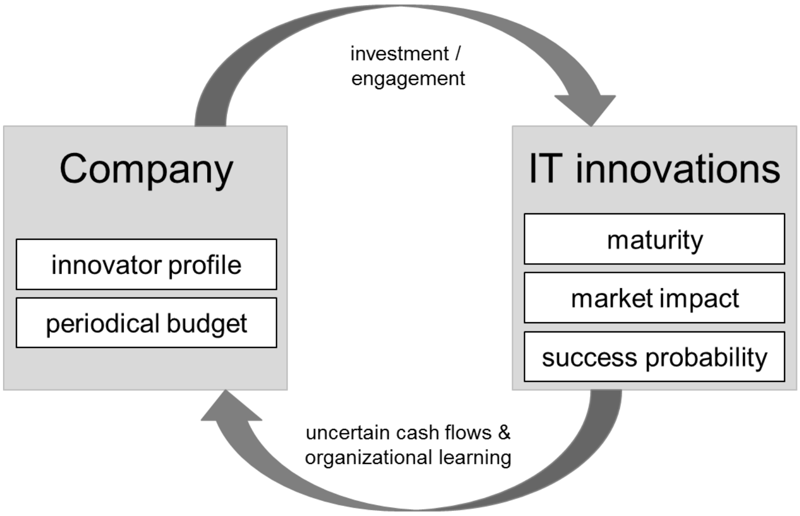

Figure 1. Influencing parameters and effects related to a company's IT innovation investment strategy

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 $t = 0, 1, \ldots, n$, 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.

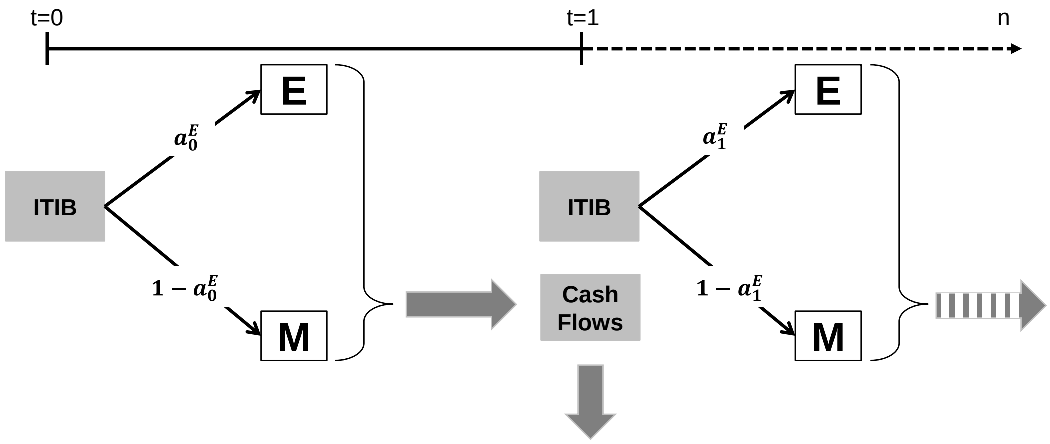

Figure 2. Decision setting over time with $t \epsilon \{0,1, \ldots, n\}$

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 $t \in \{1,2,\dots,n\}$. 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:*

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

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

w*ith 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.

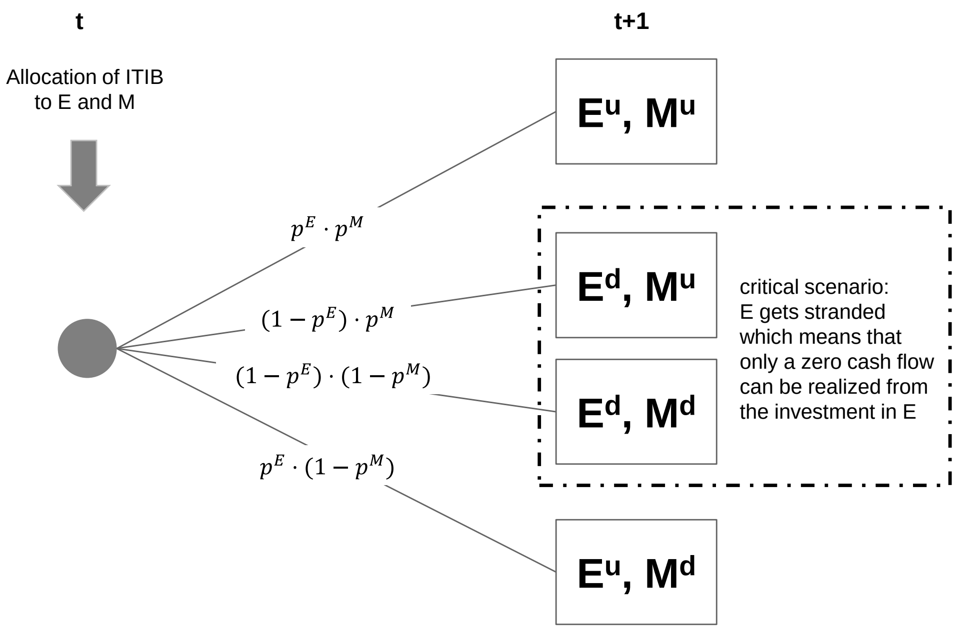

Figure 3. Scenarios for the development of the IT innovations E and M at t and $t+1$

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.

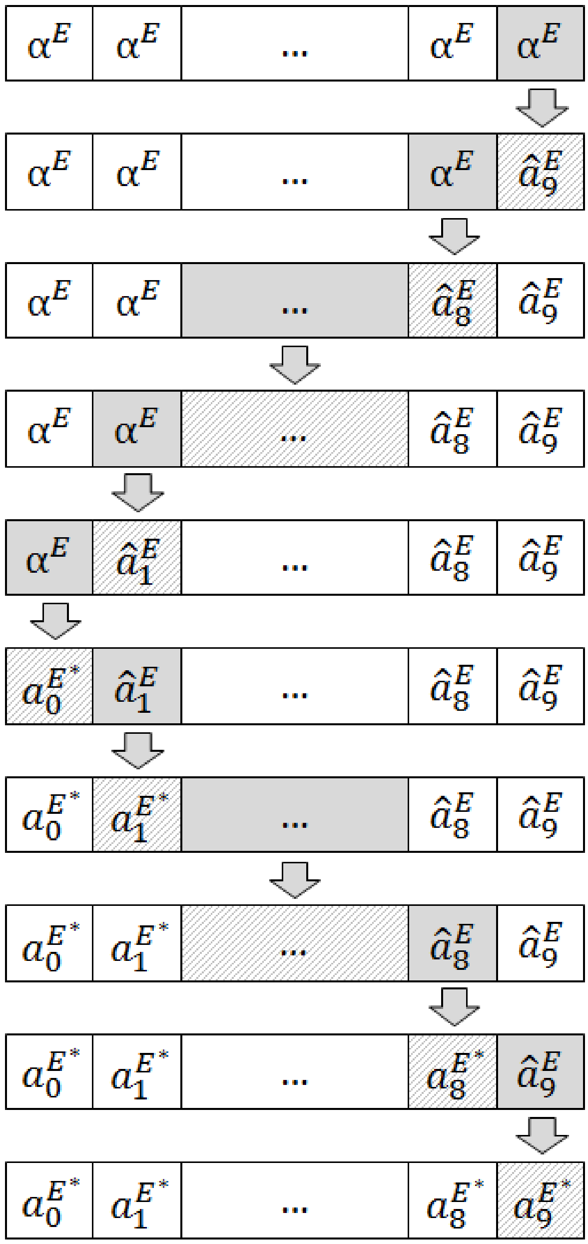

Figure 4. Schematic representation of the roll-back approach for the sequential solution of the multidimensional, dynamic optimization problem

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.

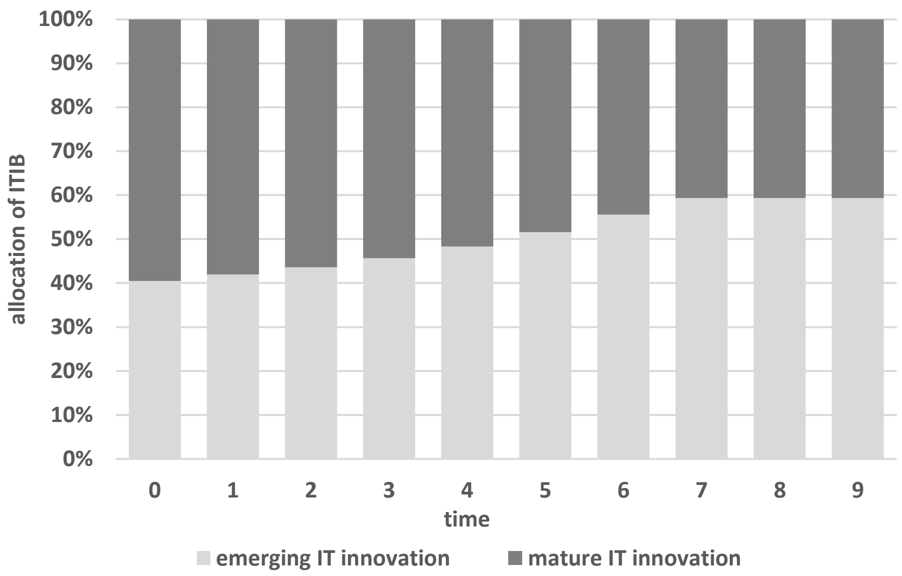

Figure 5. Optimal allocation of the IT innovation budget $ITIB$ to emerging and mature IT innovations over time

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.

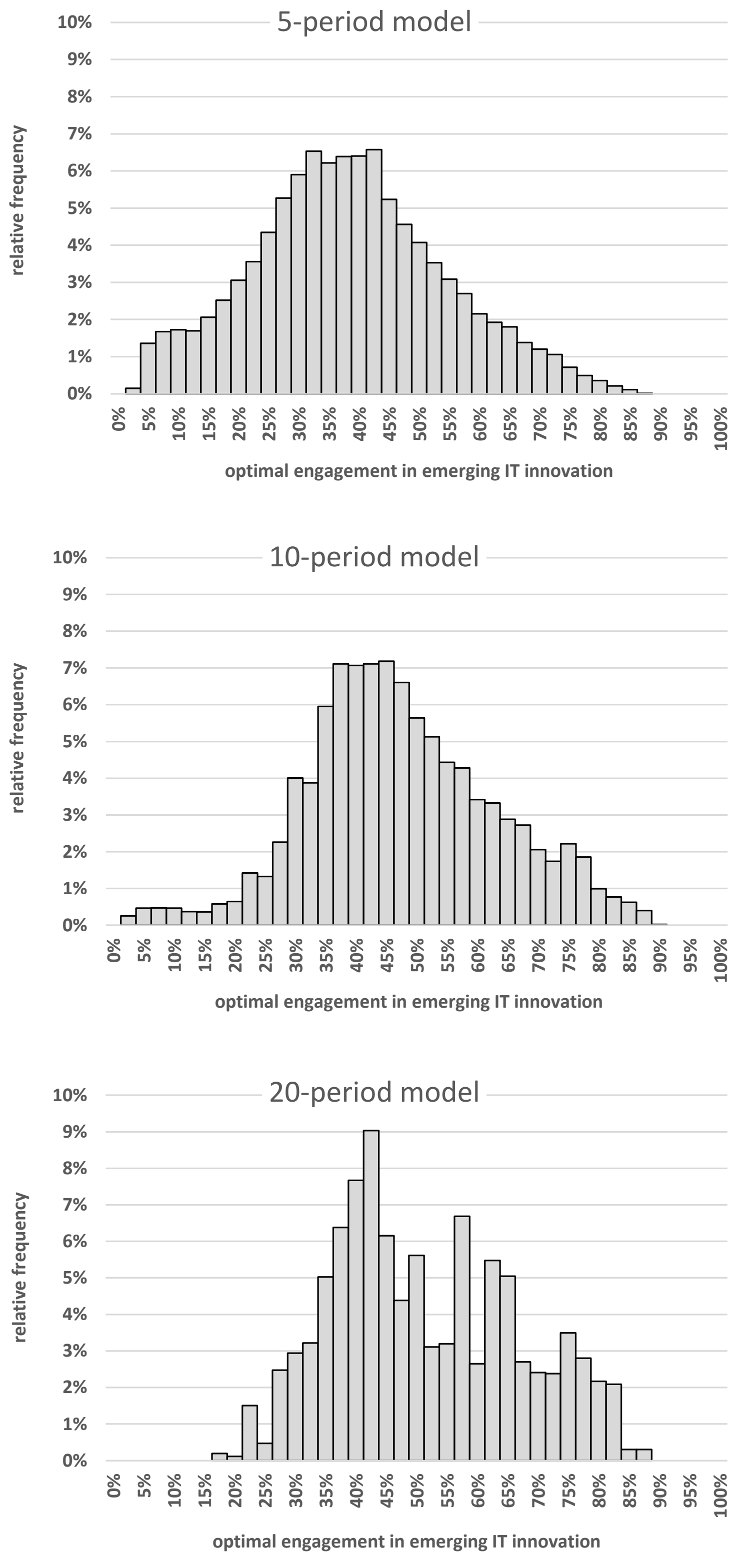

Figure 6. Histogram for $a_t^{E^*}$ for 5-period, 10-period, and 20-period models

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).

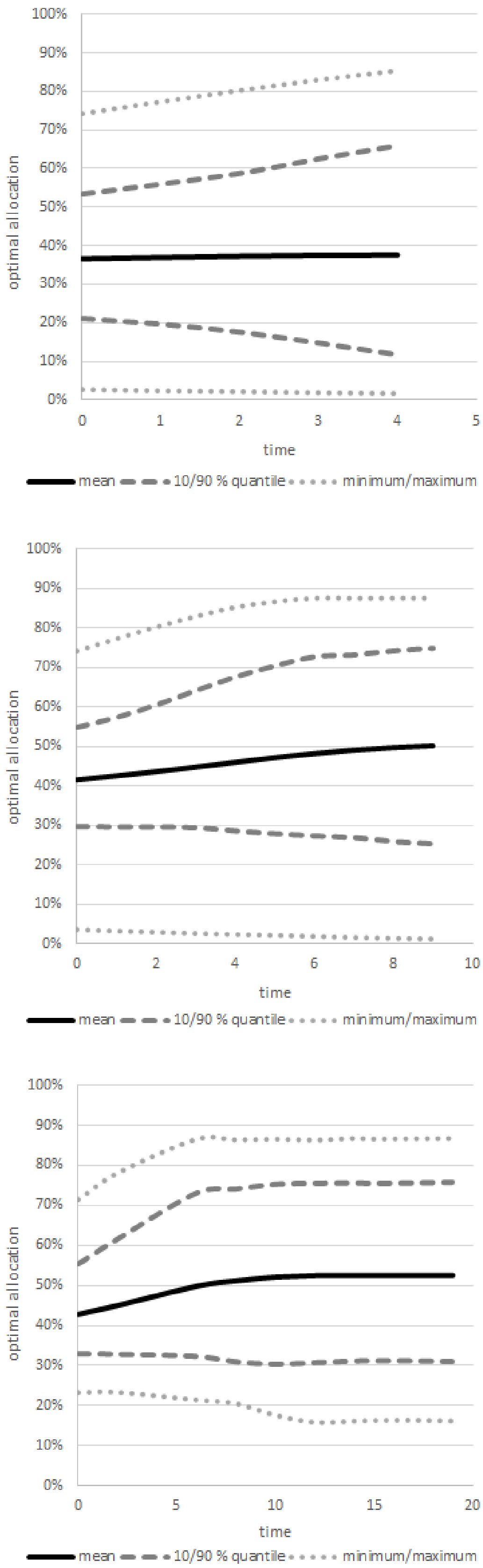

Figure 7. Results for $a_t^{E^*}$ over time after Monte Carlo simulation for 5-period, 10-period, and 20-period models

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.

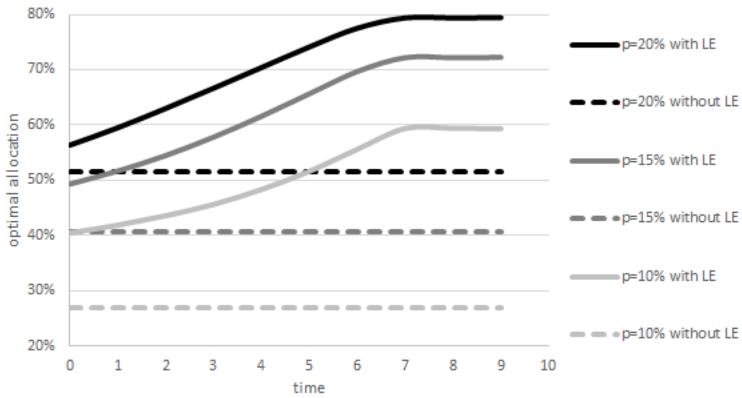

Figure 8. Optimal allocation of $ITIB$ to E with learning effect (LE) and without learning effect (LE) relative to p^E

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).

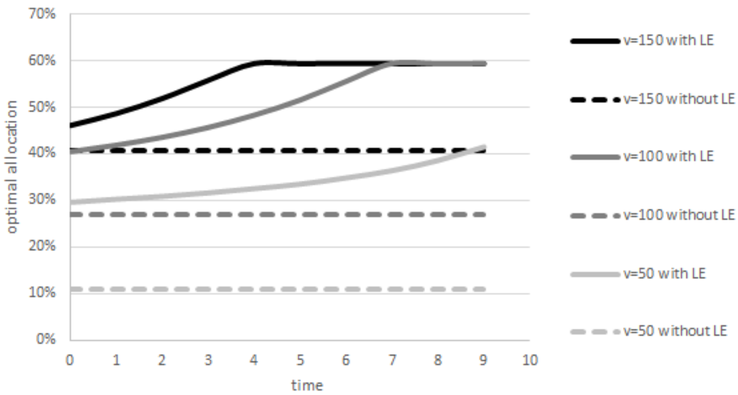

Figure 9. Optimal allocation of $ITIB$ to E with learning effect and without learning effect relative to v_0^E

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).

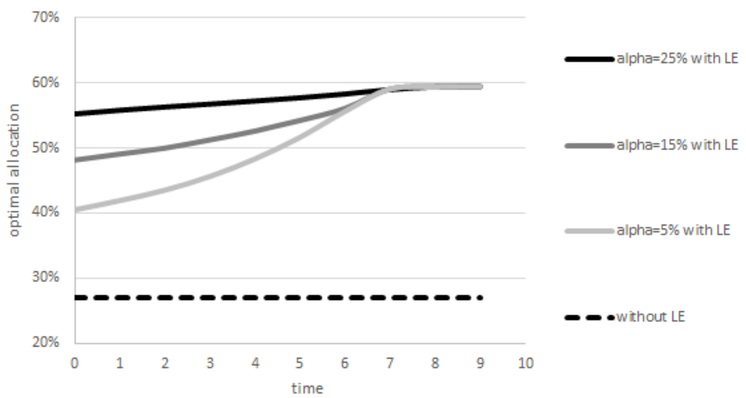

Figure 10. Optimal allocation of $ITIB$ to E and M relative to α^E

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.

II.2.7 References

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II.3 Research Paper 3: "Organizational Learning and the Error of Fixed Strategies in IT Innovation Investment Evaluation"

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Abstract:

Though many IT innovations do not meet the high expectations, the investment evaluation of fashionable IT innovations, that in contrast to mature IT innovations are currently hyped but lack broad institutionalization, often follow a gut feeling. To enhance a company's ability to innovate with IT, literature emphasizes organizational learning through continuous innovating. We extend existing IT innovation literature by developing a dynamic optimization model that determines the optimal allocation of an IT innovation budget to mature and fashionable IT innovations by considering organizational learning. As this theoretical optimum often cannot be implemented in practice, companies apply fixed strategies which seem to be suitable but do not consider the effect of organizational learning and the fashionable IT innovation's probability of success. We examine the evaluation error from under- or overinvestments in fashionable IT innovations and how this error is influenced by organizational learning and a fashionable IT innovation's probability of success.

II.3.1 Introduction

Driven by market pressure and bandwagon behavior, many companies mindlessly rush into IT innovation investments without careful consideration even though many technologies often turn out to be failing technologies (Lu and Ramamurthy 2010; Swanson and Ramiller 2004). The high uncertainty about an IT innovation's development makes it difficult for companies to know whether it will be the "next big thing" that guarantees long-term success or whether there will be just a short-term hype that will sooner or later fade away, as it was the case for the WAP technology or virtual worlds. Due to their peculiarities like uncertain success probability, literature like Wang (2010), Baskerville and Myers (2009), or Fichman (2004a) defines those IT innovations which are undergoing a hyped phase as *fashionable* IT innovations. *Mature* IT innovations, by contrast, have already been widely accepted and have a higher probability of institutionalization. Hence, IT fashion research examines technologies which need to cross the chasm from being a fashionable IT innovation to being a more mature IT innovation (Wang 2010). Due to their novelty, immaturity and thus uncertain success probability, such new emerging technologies "[…] impose significant knowledge barriers that early adopters have to overcome […]" (Ravichandran and Liu 2011).

To overcome such barriers and to enable a mindful evaluation and selection of IT innovations which are appropriate for an organization, 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 and Kemerer 1997). Organizational learning thus improves a company's innovator profile, i.e., its skills regarding the comprehension, adoption, implementation and assimilation of new technologies (Ashworth et al. 2004; Fichman and Kemerer 1997; Salaway 1987; Wang and Ramiller 2009). To improve a company's ability to thoroughly select, evaluate and thus to engage mindfully in such risky fashionable IT innovations, sufficient and continuous organizational learning requires considering fashionable IT innovations not merely as a flash in the pan but as a persistent share of the IT innovation strategy (Stratopoulos and Lim 2010; Wang 2010). At the same time, it is important for a company to incorporate the market's innovation activities into the IT innovation process to make it difficult for the market's competitors to "[…] replicate a company's ability to innovate with IT over the long term" (Stratopoulos and Lim 2010). However, even though previous empirical and qualitative research demonstrated the relationship between factors like organizational learning, IT innovation investments and the ability to innovate with new emerging IT, researchers like Williams et al. (2009) demand for more variety regarding the methodology in IT adoption and diffusion research. In particular, the question of how a fashionable IT innovation's probability of success as well as organizational learning affect the engagement in such risky IT innovations (i.e., the allocation of an IT innovation budget to fashionable IT innovations) still remains unanswered. To provide first answers in form of theoretically founded propositions on what determines an organization's engagement in mature and fashionable IT innovations, we develop a dynamic optimization model which theoretically determines the optimal investment level regarding mature and fashionable IT innovations. By taking organizational learning and the IT innovation's probability of success into account, the model is able to carve out how those factors affect the level of engagement in mature and fashionable IT innovations. As our analysis' focus throughout the paper is engagement in fashionable IT innovations, our first research question is the following:

RQ1. *How do organizational learning and a fashionable IT innovation's probability of success affect the engagement in fashionable IT innovations?*

According to our theoretical model there exists an optimal allocation of an IT innovation budget to fashionable and mature IT innovations which for a company might serve as a basis for an appropriate evaluation, selection and thus a mindful investment. However, management's uncertainty, missing data or political reasons in practice often lead to rather fixed rules within IT innovation investment strategies (Nagji and Tuff 2012; Swanson and Ramiller 2004). Nevertheless, a mindful IT innovation engagement usually requires a thorough analysis of whether a technology is appropriate for the company which cannot be realized with a fixed allocation of IT innovation budget to fashionable IT innovations. Despite the fact that previous studies have found different fixed ratios to be suitable for different industries (Nagji and Tuff 2012; Ross and Beath 2002), such fixed strategies do not consider the effect of organizational learning as they are constant over time. Thus, they might deviate from the theoretical optimum and subsequently lead to a potential evaluation error due to over- or underinvestments in fashionable IT innovations. As the optimal allocation is supposed to change over time when considering the effect of organizational learning (which also changes the company's characteristics and thus a technology's appropriateness), the evaluation error is likely to differ when applying a fixed strategy in a setting with or without the consideration of organizational learning. However, even in case a company incorporates organizational learning in its IT innovation strategy, the optimal allocation in particular still depends on a fashionable IT innovation's probability of success as well as a company's individual innovator profile. Thus, the error of over- or underinvestments due to fixed strategies is supposed to change with the fashionable IT innovation's probability of success as well as with a company's ability to innovate with IT. This raises our second research question:

RQ2. *How does a company's individual innovator profile and a fashionable IT innovation's probability of success affect the potential evaluation error of over- or underinvestments in fashionable IT innovations which results from common fixed strategies widely applied in practice?*

To approach these research questions we apply a design-science driven research, a well-recognized methodology that aims at creating and applying specific artifacts to gain knowledge of a problem domain which later might contribute to solve organizational problems (Gregor and Hevner 2013; Hevner et al. 2004; Peffers et al. 2008; Wacker 1998). Furthermore, this approach is closely related to the basic idea of the research cycle of Meredith et al. (1989), who emphasize that for research areas which have not been thoroughly examined yet, qualitative and mathematical approaches, which predict first results and propositions, provide the basis for generating hypotheses for future tests within empirical research. Hence, our research's focus is to illustrate and analyze important cause-and-effect relationships regarding two major factors which influence IT innovation investments rather than applying a normative approach that provides specific guidelines or recommendations for decision support. To reveal the effects of organizational learning and the fashionable IT innovation's probability of success on IT innovation investments as the two factors which are in focus of our analysis, we transfer central findings of IT innovation and IT fashion theory as well as aspects of organizational learning theory to a dynamic n-periods optimization model. This aims at understanding how these factors affect a company's engagement in mature and fashionable IT innovations. Knowing the theoretically optimal investment strategy allows us to analyze the potential evaluation error of over- or underinvestments in fashionable IT innovations that results from fixed investment strategies based on gut feeling decisions. Particularly, we aim at analyzing how a fashionable IT innovation's probability of success and a company's individual innovator profile affect this potential error in a model *with* as well as in a model *without* considering organizational learning. This analysis allows us to derive first propositions which build the basis for later research which aims at empirically testing the described effects. 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, IT fashion and organizational learning 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 Problem Context and Related Work

To lay the theoretical foundation for our formal-deductive mathematical model, we first provide an overview of an IT innovation's lifecycle, then critically review previous IT innovation and IT fashion research and conclude by reviewing selected aspects of the organizational learning theory.

II.3.2.1 IT Innovation Lifecycle

Within their lifecycle of adoption (Rogers 2003), IT innovations are often accompanied by waves of both, discourse (=rumor) on the innovation as well as its actual diffusion and adoption (=technical implementation) (Abrahamson and Fairchild 1999). Both waves follow a lifecycle that is closely linked to the concept of technology adoption cycles which were originally sketched by Rogers (2003) and extended into "Hype Cycles" by the firm Gartner Inc. (Fenn and Raskino 2008). This concept illustrates the start of an IT innovation's lifecycle by means of a *technology trigger* and excessive publicity leading to over-enthusiasm and investments on the basis of 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 has fashionable aspects and an unclear destiny. After this phase, opportunistic adopters often abandon ship, IT projects are scaled back and fashionable IT innovations might get stranded. Only few technologies are worth continuing and experimenting with and putting in 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 and Raskino 2008). Hence, apart from the technological risk that is associated with nearly every type of IT investment, investments in fashionable IT innovations are additionally associated with the risk of investing in a losing technology that will never be institutionalized. In the subsequent sections, we show that common IT innovation literature tends to neglect these idiosyncrasies and discuss why IT fashion research is a valuable contribution to (IT) innovation literature, especially regarding the lack of quantitative models which can support the mindful selection and evaluation of IT innovations.

II.3.2.2 IT Innovation and IT Fashion Literature

Traditional IT innovation literature mainly focuses on a set of variables like company size, structure, knowledge, or compatibility which form the company's individual innovator profile that affects the extent and ability of IT innovation adoption (Grover et al. 1997). Companies fitting this profile are expected to innovate easier, more effective and consequently more economic (Fichman 2004a). However, several authors claim to consider other IT innovation related issues (e.g., probability of institutionalization, learning by doing, impact of the technology, intensity of the market's innovativeness) in the selection and evaluation of IT innovations (Fichman 2004). Swanson and Ramiller (2004) or Fiol and O'Connor (2003) argue that companies should innovate mindfully by considering different types of IT innovations in their IT investment strategy and by deciding whether an IT innovation is appropriate for the company. This also requires a well-founded analysis of different IT innovation investment alternatives which considers the expected destiny, i.e., that some IT innovations reach institutionalization whereas some are completely abandoned.

In contrast, IT fashion theory extends the traditional focus on company size, structure, knowledge, and instead argues that the massive adoption of *certain* (IT) innovations not only is to explain through their simplicity or possible productivity increase but also through its propagation as the basis of dramatic potential improvements. Companies thereby tend to adopt (IT) innovations that are in fashion in the course of an action that is often negatively depicted as "bandwagon effect" (Abrahamson 1991; Wang 2010). Literature justifies an own IT fashion research stream by the fact that in contrast to management fashions, IT fashions often come along with high switching costs through the restructuring of IT infrastructure, tangible artifacts like software and hardware and their uniqueness due to various company individual implementation details (Fichman 2004a; Wang 2010). Lee and Collar (2003) found that IT fashions occur more frequently than management fashions what requires separate attention. Literature in IT fashion research up to now is characterized by mostly qualitative or empirical papers which deal with the development, evolution, diffusion and impact of IT fashions on companies. Dos Santos and Pfeffers (1995) demonstrated that the very early engagement in new IT can add over proportional value. Hoppe (2000) showed that under certain conditions, even second mover strategies can be advantageous due to spillover effects. Lu and Ramamurthy (2010) examined different strategies in stable and dynamic environments and showed general support for the assumption that proactive IT innovation leaders outperform reactive IT innovators in overall performance, allocation and cost efficiency. Wang (2010) found that companies that invested in fashionable IT innovations gained a better reputation and improved their performance due to over proportional returns resulting from competitive advantages in the long term. Though all this research provides valuable insights into the advantageousness of engagement in fashionable IT innovations, it stays on a rather generic level without explicitly examining how the idiosyncrasies of fashionable IT innovations might affect the optimal engagement. However, in particular the consideration of a fashionable IT innovation's risk of getting stranded plays a central role as those investments either can "[…] fail to produce the expected benefits, or indeed, any benefits at all" or "[…] could produce some benefits, but not enough to recover the costs of implementation" (Fichman 2004a). As one of the few, Kauffman and Li (2005) address this challenge and by applying a real options approach argue that within their parameterization, technology adopters are better off by deferring investments until the technology's probability to become widely accepted reaches a critical threshold of approx. 60%. The approach of Häckel et al. (2013) examines the 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 and also neglects organizational learning which is substantial for our analysis.

Only very few literature addresses the effect of organizational learning on a company's individual innovator profile and thus on the engagement in fashionable IT investments. As an example, previous research by Stratopoulos and Lim (2010) found 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 2004a). Barua and Kriebel (1995) found that those companies which 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 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).

II.3.2.3 Organizational Learning Regarding IT Innovation Investments

Swanson and Ramiller (2004) describe four core phases of the IT innovation engagement, namely *comprehension*, *adoption*, *implementation* and *assimilation*. In the *comprehension phase* a company has to learn about the IT innovation's intent and why it makes sense to adopt it. The subsequent *adoption phase* requires a solid assessment of the IT innovation's purpose, its benefits, and technical features. In this phase also the business case which accompanies the IT innovation has to be evaluated. Throughout the *implementation phase* the company has to identify its capabilities which are required to arrange the IT innovation in the company-specific context. Additionally, this requires employee's acceptance and training and, possibly, modifications of the innovation. In the *assimilation phase* the IT innovation has to be integrated into the daily business and has to be thoroughly understood to make it productive (Wang and Ramiller 2009). 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 process of comprehension, adoption, implementation and assimilation is a challenging task. Hence, organizational learning and extensive experience are particularly crucial to the outcome of the engagement in fashionable IT innovations as the introduction of new emerging technologies imposes "[…] a substantial burden on the adopter in terms of the knowledge needed to understand and use them effectively" (Weiling and Kwok Kee 2006). Certainly, the engagement in mature IT innovations also requires experience and benefits from organizational learning. However, since a lack of experience in comprehension, adoption, implementation or assimilation regarding mature IT innovations can largely be compensated by, for example, existing best practices or experiences of other companies, 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 (Ashworth et al. 2004; Fichman and Kemerer 1997; Salaway 1987; 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 - either empirically or qualitatively - emphasized that 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. 2007; Stratopoulos and Lim 2010; Swanson and Ramiller 2004; Wang and Ramiller 2009). To measure the outcome of organizational learning, previous organizational and IT innovation literature 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 can result from both, negative and positive experience (Caron et al. 1994), it is well accepted that making the experience is important "[…] even if some of that "knowledge" subsequently proves, with growing experience, to be false" (Wang and Ramiller 2009).

However, though we see a rich empirical and qualitative literature that deals with organizational learning in the context of IT innovation investments, formal-deductive and mathematical models incorporating learning aspects in the evaluation of the engagement in fashionable IT innovations are virtually absent. 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. Our model's scope is to analyze how organizational learning and a fashionable IT innovation's probability of success affect the theoretically optimal engagement in mature and fashionable IT innovations. However, companies in practice usually cannot calculate such an optimal engagement exactly and thus rather apply fixed investment strategies as emphasized by Ross and Beath (2002) or Nagij and Tuff (2012). Hence, we in a second step analyze the potential error that stems from applying such fixed investment strategies by particularly focusing on the influence of a fashionable IT innovation's probability of success as well as a company's individual innovator profile.

II.3.3 Towards 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 our artifact, a dynamic optimization model for determining the optimal allocation of a periodical IT innovation budget to mature and fashionable IT innovations. We then take this model’s result to derive theoretical propositions on how organizational learning and a fashionable IT innovation’s probability of success affect the engagement in fashionable IT innovations. According to Hevner et al. (2004), mathematical models are a common approach to represent an artifact in a structured and formalized way. For the evaluation, we in a second step combine an experimental and a descriptive design evaluation method which is a widely used approach for evaluating artifacts based on mathematical models (e.g., Wacker (1998)).

II.3.3.1 The Model

Our analysis’ focus is on the IT innovation portfolio of a company whose strategic IT innovation investments are regularly re-allocated. In every point of 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. *fashionable* IT innovations) 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: IT innovations that, according to the concept of hype cycles already reached an evolution between slope of enlightenment and plateau of productivity (Fenn and Raskino 2008) or according to Roger’s (2003) theory already are adopted by a significant amount of the market but lack mass adoption. As their evolution can be roughly estimated, no early mover advantage can be realized any more as the competitive advantage is too low due to the reached maturity. Examples for mature IT innovations that in an earlier stage experienced a fashionable phase are Customer Relationship Management (CRM) or Enterprise Resource Planning (ERP) (Wang 2010).

B) Fashionable IT innovations: IT innovations that, according to the concept of hype cycles, are in an evolutionary phase between technology trigger and trough of disillusionment and thereby fashionable (Fenn and Raskino 2008; Wang 2010). Though their long-term evolution is unclear, they are accompanied by a hype through a fashion-setting network. An engagement promises competitive first mover advantages in case of wide adoption and institutionalization. However, the technology's immaturity makes estimations about a future evolution difficult as the hype might fade away without reaching a long-term productivity. Regarding today's situation of discourse in research and practice, we can state emerging IT innovations like 3D Printing or Near-Field-Communication (NFC) technologies as fashionable IT innovations (Gartner 2012; Wang 2010).

As both types of IT innovations bear severe risks as well as tremendous opportunities, companies are well advised by incorporating future developments and consequences into their initial decision as to how much and when to invest in which kind of suitable IT innovation in order to innovate mindfully (Swanson and Ramiller 2004). Thus, to avoid gut feeling investments, methodically rigor models with initially reasonable results 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 - in the context of design-science research - the overemphasis on rigor can lessen relevance and that both paradigms, rigor and relevance, have to be relevant for all IS related research. For this reason, we need assumptions that cover crucial parts of our real world investment problem setting.

II.3.3.2 Assumptions and 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* $\mathrm{t} = 0, 1, \ldots, \mathrm{n}$, *each for one period. We define $a_t^F \in [0,1]$ 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 due to a conservative investment strategy that aims at optimizing existing products* (Hoppe 2000; Lu and Ramamurthy 2010), *we define $a_t^N = 1 - a_t^F \geq 0$ as the share of $ITIB$ that is invested in mature IT innovations (N).*

The allocation of an IT innovation portfolio's budget 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. One additional fact which is more important to our research is that 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 N.

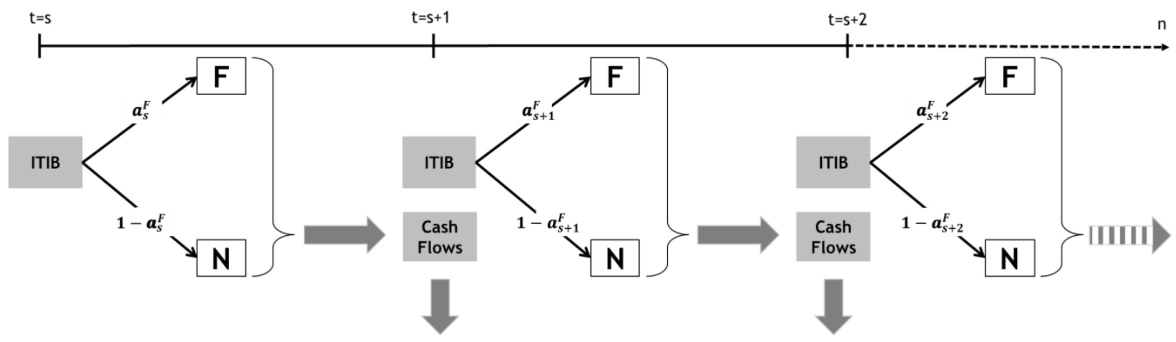

Figure 1. The investment setting at t=s, s+1, s+2

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

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

As a result, the investment alternatives F and N 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 cash flows that are realized by N and F.

Assumption 3: *The cash flows CF_t^F and CF_t^N resulting from the investments in F and N 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 $i \in [N,F]$ that was allocated to F and N, in the previous period:*

$$CF_t^i(a_{t-1}^i) = \left(a_{t-1}^i \cdot ITIB\right)^{q_z^i} \cdot v_{t-1}^i \text{ with } q_z^i \in [0,1),\, v_{t-1}^i \in R^+,\, i \in \{N,F\},\, z \in \{u,d\}$$

A monotonically increasing cash flow function is reasonable due to the fact that a higher investment in and therefore commitment to an IT innovation generally 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 (Fichman 2004a; Kimberly 1981; Melville et al. 2004). Furthermore, we can argue that an increasing investment in F or N 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 (Varian 1999). 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 (Lu and Ramamurthy 2010; Stratopoulos and Lim 2010). Moreover, due to the diminishing marginal utility of the cash flow function, a very high investment in fashionable IT innovations is not unlimited beneficial. Given that at some point the cash flow falls below the investment budget $ITIB$ which is depicted by the diminishing marginal utility, the company's engagement 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. Thus, a pure "more is better" approach might not hold true for every IT innovation investment. Furthermore, even though the cash flow function is monotonically increasing, the cash flow is limited by the limited IT innovation budget $ITIB$. Another possible way of modeling the cash flows would be a step function as certain investments require a minimum engagement (that has to go beyond an initial pilot investment which often is applied to test new emerging technologies). This would mean that a marginally increased engagement would not increase the cash flows at all as the IT innovation's next stage of expansion would require a distinctively higher engagement. However, as a step function requires the modeling of fixed investment levels as constraints which are even hard to specify in practice, we find applying a smooth cash flow function as modeled above as reasonable.

The factor q_z^i with $i \epsilon \{N, F\}$ and $z \epsilon \{u, d\}$ that is constant over time can be interpreted as a technology-specific impact factor describing the impact degree of N and F, i.e., the IT innovation's general acceptance by customers or employees, its stability, or the probability of an easy integration into the company's existing IT infrastructure, etc., that influences the investment's cash flow (Fichman 2004b; 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 N's q_z^N with $z \epsilon \{u, d\}$, i.e., $q_z^F > q_z^N \; \forall \; t = 1, \ldots, n \; with \; z \epsilon \{u, d\}$. 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 regarding an IT innovation for example can be interpreted as high acceptance by customers or employees leading to higher cash flows or institutionalization in the first place (especially for fashionable IT innovations), a downside scenario for example can be characterized by difficulties within the integration in existing processes or even the case of getting stranded (in the case of fashionable IT innovations). Therefore, we model an upside scenario as well as a downside scenario for N and F into the technology-specific impact factor, i.e., $q_u^i > q_d^i \; \forall \; t = 1, \dots, n$ with $i \in \{N, F\}$, and by that incorporate uncertainty about the IT innovation's possible outcome. Thereby, cases where the mature IT innovation in a positive scenario might have a higher impact than the fashionable IT innovation in a negative scenario, i.e. $q_d^F < q_u^N$, are possible. Though modeling only "positive" or "negative" scenarios is a rather binary view and simplifies real world scenarios that might lie somewhere in between, it incorporates the borderline cases which are of high relevance for this analysis.

The factor $v_{t-1}^i \in R^+$ with $i \in \{N, F\}$ can be interpreted as the company's individual innovator profile at t regarding mature IT investments (N) or fashionable IT investments (F). Hence, this factor generally describes the company's ability to engage in an IT innovation economically, quickly and efficiently (Fichman 2004a; Swanson and Ramiller 2004). To make an easier interpretation of the innovator profile v_t^i with $i \in \{N, F\}$ possible, we level a company that is average innovative (compared to the market) at the point in time t with $v_t^{i^*} \in R^+$, below-average innovative with $v_t^i < v_t^{i^*}$, and above-average innovative, i.e., first and progressive movers, with $v_t^i > v_t^{i^*}$, in order to transfer empirical findings by Stratopoulos and Lim (2010) as well as Lu and Ramamurthy (2010) to an analytical model. Thus, in our presented approach the individual innovator profile always 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 (Nagji and Tuff 2012; Stratopoulos and Lim 2010; Wang and Ramiller 2009) 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 of learning focuses on the engagement in fashionable IT innovations.* This focus is reasonable as, in contrast to mature IT innovations, fashionable IT innovations require a substantially higher level of experience in comprehending, adopting, implementing and assimilating new IT due to their immaturity and lack of thorough understanding and best practices. Consequently, we can narrow our analysis down to the effect of organizational learning on the company's individual innovator profile regarding fashionable IT innovations. For reasons of simplicity we assume the individual innovator profile regarding mature IT investments v_t^N to be constant over time.

Summarizing, both factors, the technology specific impact factor q_z^i with $i \in \{N, F\}$ and $z \in \{u, d\}$ as well as the company's individual innovator profile indicator factor $v_{t-1}^i \in R^+$ with $i \in \{N, F\}$ consolidate a variety of different factors. Certainly, these factors again can be split up in several sub-dimensions that might be addressed in further research. However, as we focus on a more general level and to keep the balance between rigorousness and interpretability, simplifying from reality is reasonable in this case.

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 a_{t-1}^F:*

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

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. Whereas, for example, Wang and Ramiller (2009) focus on community learning, we model a *learning by doing* (i.e., engagement in fashionable IT innovations) relation which is analogous to approaches where the required labor per produced united decreases with an increase in production (Epple et al. 1991). This means that a company experiences organizational learning through engagement in fashionable IT innovation in terms of gaining experience during the comprehension, adoption, implementation and assimilation of such a new emerging technology. Regardless of whether the fashionable IT innovation later becomes institutionalized or not, the company improves its individual innovator profile as, for the next time, it might be able to better assess, select and implement another fashionable IT innovation due to former experience. Of course, this is simplifying matter as one cannot guarantee that the (probably bad) experience made with one technology is always helpful for future investments. Thus, in case of technical leaps the previous learning about technological details might become useless for another technology. Therefore, in practice not every engagement in a fashionable IT innovation involves organizational learning as especially new emerging technologies often are very different from each other which might constrain the full spillover effect of organizational learning between different investments. Though our model implicitly assumes such a full spillover effect between all fashionable IT innovations, 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. 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 (Nagji and Tuff 2012; Stratopoulos and Lim 2010; Wang and Ramiller 2009). Therefore, we model the development of a company's individual innovator profile regarding fashionable IT innovations and thus its ability to innovate with fashionable IT in the form of a s-curve (Kemerer 1992; Raccoon 1996) as this type is the most suitable one to depict the increasing but somehow limited ability to innovate with IT. Our specific learning curve is based on the well-known logistic function and adjusted to our particular requirements. 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 modeling ensures that a company can increase its innovator profile regarding fashionable IT investments relative to the market only if it invests more in fashionable IT than the market's average does, i.e., $a_{t-1}^F > \alpha^F$. Consequently, the company's individual innovator profile decreases relative to the market in case its engagement is lower than the market average α^F, although the company might realize organizational learning through its engagement in fashionable IT innovations. Though this might not be intuitive on a first view, it 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 a rather below-innovative company. In this case, it is difficult for a company to keep pace with the market even though it finds itself very innovative. Thus, the incorporation of the market's innovativeness is important as Stratopoulos and Lim (2010) argue that for staying a systematic innovative company that outperforms the market through innovating with IT, a company requires a substantial difference in its IT innovation activities compared to the competitors. The growth rate β thereby 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. Thus, the learning curve depends on the extent of the engagement in fashionable IT (regardless of whether they will be successful or not) (Caron et al. 1994). In addition to the learning curve we restrict the innovator profile to a global upper limit G. In reality, the company will - at some point - reach a level of saturation of innovativeness, which impedes the possibility to gain infinite knowledge and innovativeness. A reasonable value for G might be two times the average market innovator profile $v_t^{F^*}$. To sum up, our approach of modeling organizational learning certainly simplifies from reality and inherits the assumption that engaging in fashionable IT innovations simply increases organizational learning. However, as our model aims at providing first propositions which later can be tested empirically rather than a one-to-one application to real-world business problems, modeling the development of a company's innovator profile in this way seems appropriate for the purpose of this paper.

Assumption 5: *The IT innovation's lifecycle - as described above - 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 (i.e., technology trigger, peak of inflated expectations and trough of disillusionment) and $t = s + 1$ describes the point of time when its destiny turns out (slope of enlightenment with institutionalization or failing). Consequently, in case that a fashionable IT innovation becomes institutionalized (=mature), $t = s + 2$ describes its plateau of productivity's altitude. In case of a mature IT innovation, the time frame illustrates its impact over two periods. 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 definitely 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 a company's IT innovation 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). In addition, limiting the time frame to two periods makes it possible to keep the mathematical model as simple as possible by not limiting the central propositions for research and practice at the same time.

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 $i \epsilon \{N, F\}$ 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 $i \epsilon \{N, F\}$ via a binomial distribution.*

Though different fashionable IT innovations in reality are likely to be characterized by different probabilities regarding institutionalization, we for reasons of simplicity assume the probabilities $\mathrm{p^i}$ with $\mathrm{i} \epsilon \{\mathrm{N}, \mathrm{F}\}$ to be constant over time. However, as constant probabilities do not disturb the general results of our model and varying probabilities might only pretend improved accuracy of measurement, constant probabilities as assumed are justifiable. Hence, p^i with $i \epsilon \{N, F\}$ describes the possibility that an investment in N creates the desired cash flows (N^u with $\mathrm{q_u^N}$) 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 $\mathrm{q_u^F}$). By means of $1 - p^i$ with $i \epsilon \{N, F\}$ we describe the probability that an investment in N will create below-average cash flows (N^d with $\mathrm{q_d^N}$) 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 $\mathrm{q_d^F}$).

IT fashion literature assumes companies to engage in fashionable IT innovations due to two major reasons: Whereas the economic-rationalistic perspective focuses on the organizational performance in terms of financial returns, the institutional perspective stresses organizational legitimacy reasons as an important factor (e.g., pressure of other companies) (Wang 2010). As our approach aims at providing insights that avoid an engagement in fashionable IT innovations on a gut feeling, we focus on the first perspective and thus financial aspects as key decision criteria which is depicted in the following assumption.

Assumption 7: *The company is a risk-neutral decision maker that 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 risk-free interest rate $r \epsilon [0,1]$ that is assumed to be constant for each period.*

Assuming a risk neutral decision maker who decides on the basis of the expected value of a company's IT innovation portfolio is reasonable as the IT innovation portfolio's scope is to do basis research for discovering long-term value. Hence, an IT innovation portfolio, by definition, deals with riskier investments than, for example, an IT asset portfolio, which deals with infrastructure, operational data and routine processes (Maizlish and Handler 2005; Ross and Beath 2002). Assuming a risk-averse decision maker is due to further research regarding the question of how the explicit consideration of the risk/return trade-off affects the engagement in fashionable and mature IT innovations. However, we do not expect the general cause-and-effect relationships among the crucial factors to change distinctively in a model that considers a risk-averse investor.

Cash Flows at t: A fashionable IT innovation can turn out to be both, a failing technology (i.e., a downside scenario with $\mathrm{q}_{\mathrm{d}}^{\mathrm{F}}$ even leads to zero cash flows at $t = s + 1$) and a groundbreaking technology (i.e., an upside scenario with $\mathrm{q}_{\mathrm{u}}^{\mathrm{F}}$ results in extraordinary high cash flows for early movers). Therefore, its cash flows at $t = s + 1$ and $t = s + 2$, after the hype around the technology has waned, are of particular interest to the analysis (Fenn and Raskino 2008; Fichman 2004a). Regarding the mature IT innovation we also have to 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 N at $t = s$ can result in the following cash flows $\mathrm{CF}_{\mathrm{t}}^{\mathrm{F}}$ or $\mathrm{CF}_{\mathrm{t}}^{\mathrm{N}}$ with $t = s + 1$ and $t = s + 2$:

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

		$\mathrm{t = s + 1}$	$\mathrm{t = s + 2}$
Upside scenario (p^i) with $\mathrm{i} \in \{\mathrm{N, F}\}$	F	$(\mathrm{a_s^F} \cdot \mathrm{ITIB})^{\mathrm{q_u^F}} \cdot v_s^F$	$(\mathrm{a_{s+1}^F} \cdot \mathrm{ITIB})^{\mathrm{q_u^F}} \cdot v_{s+1}^F$
	N	$(\mathrm{a_s^N} \cdot \mathrm{ITIB})^{\mathrm{q_u^N}} \cdot v_s^N$	$(\mathrm{a_{s+1}^N} \cdot \mathrm{ITIB})^{\mathrm{q_u^N}} \cdot v_{s+1}^N$
Downside scenario $(1 - p^i)$ with $\mathrm{i} \in \{\mathrm{N, F}\}$	F	0	$(\mathrm{a_{s+1}^F} \cdot \mathrm{ITIB})^{\mathrm{q_d^F}} \cdot v_{s+1}^F$
	N	$(\mathrm{a_s^N} \cdot \mathrm{ITIB})^{\mathrm{q_d^N}} \cdot v_s^N$	$(\mathrm{a_{s+1}^N} \cdot \mathrm{ITIB})^{\mathrm{q_d^N}} \cdot v_{s+1}^N$

To enable an ex ante analysis on how the engagement in fashionable IT innovations (i.e., the allocation of the IT innovation budget $ITIB$ at t to fashionable IT innovations) is affected by organizational learning and the probability of success, we determine the allocation of $ITIB$ that maximizes the IT innovation portfolio's expected net present value (NPV). Hence, the objective function of the dynamic optimization problem is as follows:

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

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

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 N and perform a roll-back (i.e., dynamic programming according to Bellman (1957)) analysis (Clemons and Weber 1990; Magee 1964; Suleyman 1993). For the evaluation we choose a planning horizon of ten 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 by ensuring reasonable simulation runtimes at the same time. 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 interrelationships between variables, and the optimization over the possible decisions (Bonini 1975). A real option approach as applied by Kauffman and Li (2005) or Fichman (2004) might also have been suitable to address this decision setting but inherits restrictive assumptions as the existence of a twin security, and so is not suitable for an ex ante allocation of an IT Innovation budget. Though acquiring real world data to examine the benefits of our theoretic approach profoundly is rather difficult, considerable advantages for the evaluation can be realized when knowing how the engagement in fashionable IT innovations might be affected by various factors. 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 simulation's parameter ranges which are relevant for the simulation. For the sake of simplicity we assume equal distributions for all parameters as other distributions, such as the Gaussian, would not distort the general conclusions but increase complexity. Analogous to Kauffman and Li (2005) we take $r = 0.1$ for the risk-free interest rate and $v_t^{N^*} = 100$ for the company's individual innovator profile regarding mature investments. We generally start our analysis with rather conservative values and also let the relevant parameters range in conservative intervals to avoid distortion due to overoptimistic value estimations. To demonstrate the impact of organizational learning on investment evaluation regarding fashionable IT innovations, our simulations generally include a comparison between the optimal IT innovation budget's allocation resulting from the model *with learning effect* to the model *without learning effect*. Additionally, we analyze the potential error that occurs from deviating from the theoretical optimum by applying a fixed investment strategy.

Table 2. Data for Monte Carlo simulation

Parameter	Range
Company's individual innovator profile v_0^F	50 – 150
Fashionable IT innovation's impact factor q_u^F (upside scenario)	0.25 – 0.50
Mature IT innovation's impact factor q_u^N (upside scenario)	0.20 – 0.40
Probability that fashionable IT innovation will create desirable cash flows p^F	0.05 – 0.15
Probability that mature IT innovation will create desirable cash flows p^N	0.15 – 0.30
Average engagement of the market α^F	0.05 – 0.15

II.3.4.1 The impact of a company's initial innovativeness v_0^F on the optimal investment strategy

In the first place, we simulate 500 different scenarios and analyze the average optimal investment strategy for a below-average innovative company (with $v_0^F = 50$), an average innovative company (with $v_0^F = 100$) and an above-average innovative company (with $v_0^F = 150$). Given this parameter setting and the justifiable assumptions mentioned above, our first proposition is that the optimal engagement a_t^F in fashionable IT innovations increases with the company's innovativeness and changes dynamically over time as shown in Figure 2. Within this setting, we observe that a below-average innovative company which aims at maximizing the expected NPV can reach this by slowly increasing the engagement in fashionable IT innovations over time. This can be explained by organizational learning through engagement in fashionable IT innovations which improves the future ability to innovate with IT. We observe a similar situation for an average innovative company except that the range of 16.58% between the lowest and the highest value for a_t^F over time substantially exceeds the range of 7.55% for a below-average innovative company. Thus, we assume that an average innovative company might clearly benefit from organizational learning resulting in a distinct increase of the engagement in fashionable IT innovations over time. In contrast, our analysis reveals that the investment strategy of a below-average innovative company does change less over time compared to the investment strategy of an above-average or average innovative company as it will hardly reach the innovativeness of the market average despite the positive effects of organizational learning. Regarding an above-average innovative company, we observe an engagement which increases in early points of time as seen for an average innovative company. However, it levels off at a constant level as soon as the maximal and limited innovativeness is reached. Consequently, the range of 10.57% regarding the development of a_t^F over time shrinks compared to the range for an average innovative company but still exceeds the range for a below-average company.

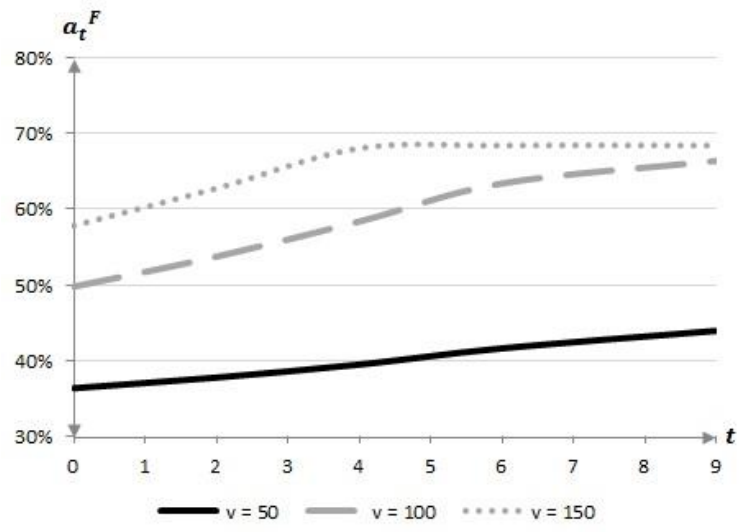

Figure 2. The average optimal investment strategy relative to a company's initial innovator profile.

Within this analysis, an average innovative company dynamically adjusts its engagement in fashionable IT due to organizational learning. Furthermore, a below-average innovative company is considerably less affected by organizational learning and therefore also the optimal investment strategy is rather fixed over time. We also notice that an above-average innovative company scales its engagement at first, but sooner or later changes to a constantly high investment strategy and keeps it fixed over time. Though our model enables us to determine an optimal ex ante IT innovation investment strategy from a theoretical point of view, companies in practice should individually select IT innovations regarding the appropriateness to the company (Swanson and Ramiller 2004).

Additionally, individual company profiles, high estimation uncertainty regarding model parameters or political reasons might impede a direct transfer to real world business decisions. This in practice often leads to fixed IT innovation investment strategies for different kinds of (IT) innovations for different industries (Nagji and Tuff 2012; Ross and Beath 2002). However, 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. Taking our model, for each simulation run i with $i \in \{1, \dots, 500\}$ we can determine the evaluation error $\Delta_{i,j}^{err}$ by comparing the IT innovation portfolio's optimal NPV_i^{opt} with the $\text{NPV}_{i,j}^{fix}$ that results from applying a certain fixed investment strategy j (i.e., j represents one possible fixed combination of allocating the IT innovation budget with e.g., $a_t^F = 40\%$ and $a_t^N = 60\%$):

$$\Delta_{i,j}^{err} = \frac{\text{NPV}_i^{opt} - \text{NPV}_{i,j}^{fix}}{\text{NPV}_i^{opt}}$$

To examine the extent of the evaluation error, we change the engagement a_t^F and so obtain different fixed strategies j. For every fixed strategy j, we calculate the *average evaluation error* $\Delta_{avg,j}^{err}$:

$$\Delta_{avg,j}^{err} = \frac{1}{500} \cdot \sum_{i=1}^{500} \Delta_{i,j}^{err}$$

In the following, we illustrate $\Delta_{avg,j}^{err}$ depending on the engagement in fashionable IT Innovations, i.e., the potential economic error that arises from applying a fixed strategy regarding the allocation of an IT innovation budget to fashionable IT innovations (as we only consider two investment alternatives, a fixed engagement a_t^F at once determines the engagement a_t^N in mature IT innovations). In a first step, we examine the impact of a company's initial innovativeness on the potential error that occurs from applying a fixed investment strategy regarding fashionable IT innovations. For that, we calculate the average evaluation error for an initially below-average innovative company (with $v_0^F = 50$), an initially average innovative company (with $v_0^F = 100$) and an initially above-average innovative company (with $v_0^F = 150$). In another simulation we aim at examining the impact of a fashionable IT innovation's probability of success on the potential error that occurs from applying a fixed investment strategy regarding fashionable IT innovations. For that, we assume an average innovative company with $v_0^F = 100$ and calculate the average evaluation error that arises in scenarios with a probability of success for a fashionable IT innovation of $p^F = 5\%$, $p^F = 10\%$, and $p^F = 15\%$. To illustrate the effect of organizational learning, we additionally repeat all the described simulations and analyses for the same model setting *without* the effect of organizational learning and compare the results.

II.3.4.2 The impact of a company's initial innovativeness $\boldsymbol{v_0^F}$ on the potential error from fixed investment strategies

As might be expected, a company's initial innovator profile v_0^F not only affects the optimal allocation of an IT innovation budget to fashionable IT innovations but also the evaluation error that occurs from applying a fixed investment strategy regarding fashionable IT innovations. In Figure 3 we illustrate the average evaluation error $\Delta_{avg,j}^{err}$ for all possible fixed investment strategies regarding fashionable IT innovations for companies with different initial innovativeness in a model with organizational learning. Figure 4 illustrates $\Delta_{avg,j}^{err}$ in a model without organizational learning.

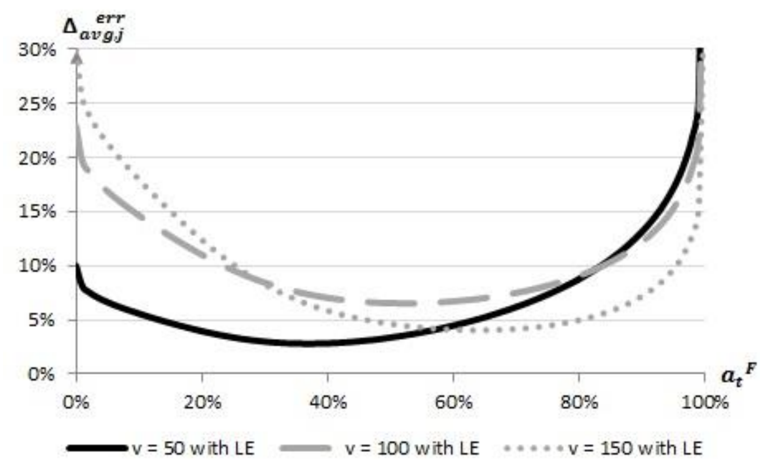

Figure 3. Average evaluation error $\Delta_{avg,j}^{err}$ for companies with different initial innovativeness in the model *with* learning effect.

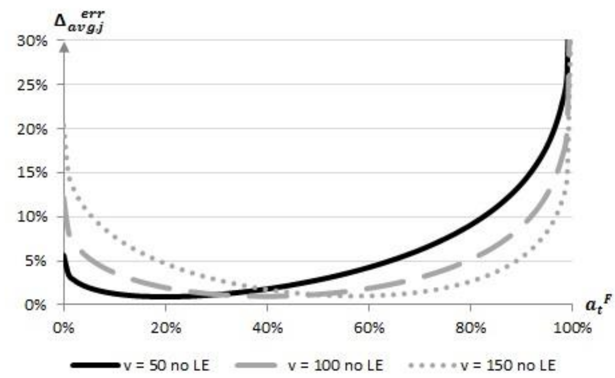

Figure 4. Average evaluation error $\Delta_{avg,j}^{err}$ for companies with different initial innovativeness in the model *without* learning effect.

The global minimum of each curve represents the fixed investment strategy j^* where the average evaluation error is minimal. Regardless whether we apply a model with or without considering the effect of organizational learning, the results of our analysis which we can observe in Figure 3 and Figure 4 let us assume that companies with a higher initial innovativeness are better off by allocating a higher fixed share of their IT innovation budget to fashionable IT innovations than companies with a lower initial innovativeness. This is illustrated by the fact that for companies with higher initial innovativeness the minimal average evaluation error occurs at a higher fixed engagement j. As we focus on only two types of IT innovations (mature and fashionable) and also consider the effect of organizational learning, our analysis which results in allocating approx. 50% to fashionable IT innovations for an average innovative company cannot be matched with the results from former literature (Nagji and Tuff 2012; Ross and Beath 2002) which found that allocating about 15% in fashionable IT innovations seems reasonable. However, previous literature usually incorporated more than two types of IT innovations and furthermore neglected organizational learning which might explain the considerably lower engagement in fashionable IT innovations. This is underlined by the analysis of the model without considering organizational learning, which shows distinctly lower values compared to the model considering organizational learning (20% vs. 37% for $v_0^F = 50$). This results from the effect of organizational learning as operationalized in our model which encourages companies to increase their engagement in fashionable IT innovations in order to benefit from subsequent investments (Ashworth et al. 2004; Salaway 1987; Wang and Ramiller 2009). Besides, our research approach's focus is on illustrating important cause-and-effect relationships regarding the factors which influence the engagement in IT innovation investments. Thus, in contrast to previous research within this area (Nagji and Tuff 2012; Ross and Beath 2002), we aim at providing general insights for companies regarding important factors to consider rather than specific values as rule of thumb. Interestingly, the average evaluation error's absolute extent that arises from the fixed investment strategy with the smallest difference compared to the optimal investment strategy strongly differs with the company's initial innovativeness. Looking at the three curves from the model with learning effect (Figure 3), we can observe that Δ_{avg,j^*}^{err} varies from 2.79% (for $v_0^F = 50$) to 6.52% (for $v_0^F = 100$). The relatively small error for a below-average innovative company with $\Delta_{avg,j^*}^{err} = 2.79\%$ can be explained by the fact that given our model setting and parameterization, we suggest the optimal investment strategy almost to be fixed over time for such companies as seen in Figure 2. With an initial average innovativeness of $v_0^F = 100$, the minimal evaluation error in our analysis increases considerably ($\Delta_{avg,j^*}^{err} = 6.52\%$) as we observe that the optimal investment strategy changes distinctively more over time for these companies. For above-average innovative companies with $v_0^F = 150$, we can observe that the minimal average evaluation error decreases to $\Delta_{avg,j^*}^{err} = 4.04\%$ compared to the error for average innovative companies. This matches with the results from the first analysis where we showed that the engagement in fashionable IT innovations does not change as much over time for above-average innovative companies.

In the model without learning effect (Figure 4), we observe a minimal average evaluation error which is substantially lower compared to the model with learning effect for all initial innovator profiles and also does not change across the different initial innovator profiles. This results from the fact that in this setting, an engagement in fashionable IT innovations at a certain point of time does not influence the subsequent decisions and thus, the optimization problem is not dynamic anymore. Hence, the fixed investment strategy with the lowest evaluation error at the same time is the theoretical optimum. The minimal *average* evaluation error of approx. 1% is explained by calculating the average over the 500 simulations. However, the smaller minimal average evaluation error compared to a model with organizational learning shows that the optimal investment strategy does not change dynamically over time. This lets us assume that neglecting the effect of organizational learning can lead to a miscalculation of a company's optimal investment strategy.

As allocating the IT innovation budget in a manner so that the average evaluation error compared to a theoretical optimum hits the minimum is rather complex or even impossible, it is highly relevant to know whether an over- or underinvestment compared to the theoretical optimum results in a higher potential error. The results of our model which are illustrated in Figure 3 and Figure 4 show some general trends about the average evaluation error and thus the disadvantageousness of an over- or an underinvestment. Figure 3 lets us assume that over- and underinvestments result in higher evaluation errors compared to the model that does not consider the effect of organizational learning (Figure 4). Hence, we propose that both, over- and underinvestments are equally disadvantageous in a model considering organizational learning.

To sum it up, given the model setting and the parameter values within the simulation, the second part of our analysis makes us assume that in case of neglecting the effect of organizational learning, a fixed investment strategy regarding fashionable IT innovations does not lead to substantially worse results than applying the theoretically optimal investment strategy. This might be reasoned by the fact that calculating the optimal investment strategy while not considering organization learning probably always leads to a fixed investment strategy. However, the consideration of organizational learning - which clearly better illustrates the real world - in our model shows considerably larger differences between the theoretical optimum and a fixed investment strategy. Thus, we propose that according to our model, companies probably are better off by adjusting their IT innovation budget’s allocation over time instead of applying a fixed strategy.

II.3.4.3 The impact of a fashionable IT innovation’s probability of success p^F on the potential error from fixed investment strategies

Even the most innovative company with high ability to innovate with new IT likely profits from incorporating the success probabilities of fashionable IT innovations into its investment strategy as we assume them to substantially affect the expected payoff. Thus, we conduct another simulation and analyze the fashionable IT innovation’s probability of success as a parameter of major importance and impact. For this analysis, we hold the initial innovator profile constant at the average value of $v_0^F = 100$ (as we observed the highest volatility regarding the dynamic adjustment of the investment strategy and the evaluation error for this parameterization in our first analysis) and calculate the average evaluation error for fixed investment strategies regarding fashionable IT innovations with an extremely low ($p^F = 5\%$), a medium high ($p^F = 10\%$) and a considerably high ($p^F = 15\%$) probability of success in order to analyze the evaluation error. Figure 5 and Figure 6 show the results of the simulation for a model with and model without organizational learning analog to the Figures above.

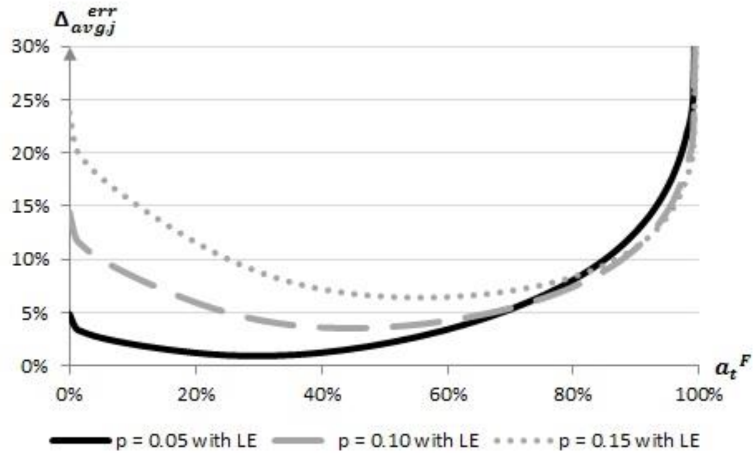

Figure 5. Average evaluation error $\Delta_{avg,j}^{err}$ for fashionable IT innovations with different probability of success in the model *with* learning effect.

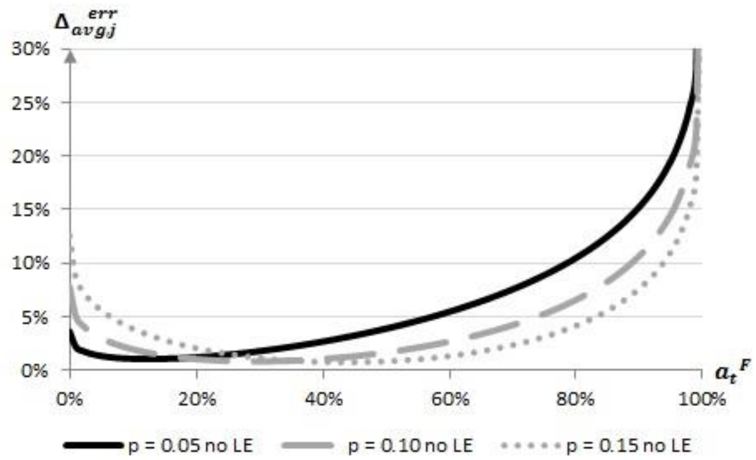

Figure 6. Average evaluation error $\Delta_{\mathrm{avg,j}}^{\mathrm{err}}$ for fashionable IT innovations with different probability of success in the model *without* learning effect.

The curves in Figure 5 show that with a higher probability of success, the average evaluation error that arises from the fixed investment strategy with the lowest deviation from the theoretical optimum increases for the model considering organizational learning. This is reasonable as a high probability of success given our model assumptions implies a higher engagement in fashionable IT innovations and therefore a higher learning effect which as aforementioned leads to a more dynamic optimal investment strategy over time. This dynamically changing strategy with a higher engagement differs more strongly from a strategy that is constant over time. In analogy to the analysis above, our results let us assume over- and underinvestments to be considerably more disadvantageous in a model considering organizational learning. Figure 6 shows the results for the model without learning effect which are very close to the simulation results regarding different initial innovativeness.

To sum it up, the probability of success in our model substantially influences the evaluation error that results from fixed investment strategies which deviate from the theoretical optimal when considering the effect of organizational learning. Also, our results let us assume that the effect of organizational learning has to be considered when deciding on the engagement in fashionable IT innovations. The neglect of organizational learning according to our results might result in time-constant investment strategies which lead to substantially worse results than a theoretical optimum which changes dynamically over time.

II.3.5 Theoretical and Practical Implications and Limitations

Decisions on investments in new emerging IT innovations that are in a hyped phase (=fashionable IT innovations) often do not follow a thorough analysis but rather a gut feeling. In this context, organizational learning plays an important role to improve the company’s individual innovator profile and thus the ability to innovate with new emerging IT. Our model aims at providing first insights in how organizational learning and a fashionable IT innovation’s probability of success affect investments in fashionable IT innovations. We thus contribute to IT innovation and organizational literature by developing a mathematical model which incorporates issues related to IT innovations (e.g., probability of success, intensity of competition) as well as company characteristics (e.g., ability to innovate, organizational learning). Though in practice, companies usually should look at any IT innovation individually and then mindfully decide on whether it is appropriate to invest, such mathematical models can support the process of selection and evaluation by emphasizing and illustrating crucial cause-and-affect relationships. For that, we develop a dynamic n-periods optimization approach that optimizes the allocation of a periodical IT innovation budget to different types of IT innovation by considering organizational learning. Our analysis shows that there is a theoretical optimum which changes over time and which mainly depends on the fashionable IT innovation's success probability as well as the company's individual innovator profile. However, this theoretical optimal allocation in practice hardly can be implemented due to management's uncertainty, missing data or political reasons. Companies thus often apply fixed rules within IT innovation investment strategies which seem to be suitable but neglect the effect of organizational learning (Nagji and Tuff 2012; Ross and Beath 2002). We in particular examine the evaluation error that stems from applying such fixed strategies which do not incorporate the effect of organizational learning, thus are constant over time and so deviate from the theoretical optimum. Taking our theoretical model including its justifiable but also arguable assumptions, our analysis method as well as its parameters' value, our results make us suggesting the following propositions as a basis for further research and practice:

- Independently from a company's ability to innovate, the substantial engagement in fashionable IT innovations can be beneficial.
- Depending on a company's initial ability to innovate, the extent of how an optimal engagement in fashionable IT innovations dynamically changes over time, is different. An average innovative company's optimal allocation is likely to adjust the most over time.
- For below-average innovative companies which according to our results have the smallest change of their optimal allocation over time, applying a fixed strategy regarding the allocation of the IT innovation budget and thus deviating from the theoretical optimum results in the smallest evaluation error.
- Neglecting the effect of organizational learning probably leads to a miscalculation of a company's individual optimal investment strategy as the optimal allocation does not change over time. Thus, the evaluation error that stems from applying fixed strategies and thus from an over- or underinvestment compared to the theoretical optimum is higher when considering organizational learning.
- The higher a fashionable IT innovation's probability of success regarding long-term institutionalization, the higher the evaluation error that stems from applying a fixed strategy.

Our model aims at providing first insights and propositions which might be the basis for empirical validation and useful in further research approaches. Thus, we do not provide decision making guidance which is directly transferable to practice. Further research which in a first step empirically validates the described relationships and in a second step operationalizes the findings in a model that allows for concrete decision support thus might deliver valuable support for business problems. For that, the following aspects which are not covered yet by our approach need to be addressed in future research: 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, empirically testing the model and its parameters as different dimensions of q or v with real world data is due to further research. Also, the model's inherent interpretation of the IT innovation's value is limited to quantifiable components of value. So far, minimum or maximum investments are not considered yet as well as incorporating risk interdependencies between different IT innovations. Our model focuses on the economic-rationalistic perspective, thus is based on financial aspects and for that assumes a risk-neutral decision maker who decides on the basis of expected values. This approach neglects the possibility of IT innovation investments based on legitimacy issues rather than an assessment of risk and return and also does not address risk-averse behavior. A differentiation between certain specific fashionable and mature IT innovations and considering different success probabilities additionally bears potential for further research. Also, companies might engage in fashionable IT innovations to ensure only competitive parity instead of aiming at competitive advantage or first mover advantages which would require a more game-theoretic approach. Also, 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 investment strategy when considering fashionable technologies. Moreover, it is a theoretically sound economic approach which allows further development and provides insights into IT innovation related issues. Grounding on design-science research, it serves as a basis for future research and aims at addressing "[…] important unsolved problems in unique or innovative ways […]" (Hevner et al. 2004) to contribute to the understanding and improvement of IT fashion research as "[…] IS researchers should be among the leaders, and not just the followers, of fashion" (Baskerville and Myers 2009).

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III Decision Support in Credit Portfolio Management Considering Risk and Return

III.1 Research Paper 4: “Multivariate Credit Portfolio Management Using Cluster Analysis”

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Structured Abstract:

Purpose

This paper aims to improve decision making in credit portfolio management through analytical data-mining methods, which should be used as data availability and data quality of credit portfolios increase due to (semi-)automated credit decisions, improved data warehouses, and heightened information needs of portfolio management.

Design/methodology/approach

To contribute to this fact, this paper elaborates credit portfolio analysis based on cluster analysis. This statistical method, so far mainly used in other disciplines, is able to determine “hidden” patterns within a dataset by examining data similarities.

Findings

Based on several real-world credit portfolio datasets provided by a financial institution, we find that cluster analysis is a suitable method to determine numerous multivariate contract specifications implying high, respectively low profit potential.

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Research limitations/implications

Nevertheless, cluster analysis is a statistical method with multiple possible settings that have to be adjusted manually. Thus, various different results are possible and as cluster analysis is an application of unsupervised learning, a validation of the results is hardly possible.

Practical implications

By applying this approach in credit portfolio management, companies are able to utilize the information gained when making future credit portfolio decisions and, consequently, increase their profit.

Originality/value

The paper at hand provides a unique structured approach on how to perform a multivariate cluster analysis of a credit portfolio by considering risk and return simultaneously. In this context, this procedure serves as a guidance on how to conduct a cluster analysis of a credit portfolio including advices for the settings of the analysis.

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III.1.1 Introduction

The active management of credit risk is the core competence of banks because no other market participant has superior knowledge and experience in relation to the management of credit risk of the customers (Henking et al., 2006). The use of more advanced techniques for risk management is necessary due to the globally increasing credit exposures of financial institutions (J.P. Morgan, 1997). Therefore, e.g. J.P. Morgan introduced more sophisticated measures like a value-at-risk framework for credit risk and percentile levels e.g. showing the lowest level of the portfolio that it will achieve in 1% of the cases. Yi and Gang (2008) state that the application of classification, clustering and other data mining techniques are becoming more interesting for practitioners and researchers in recent years. They summarize that the implementation of an appropriate evaluation of financial risk within the risk management practices of guarantors and financial institutions may increase the revenue and may reduce the loss. Besides the evaluation of the underlying risk structure, a consideration of the return potential is desirable, as it leads to further insight into the portfolio structure. An integrated approach for credit management, which considers a return and a risk measure equally, could reveal further credit portfolio optimization potential because in-depth knowledge gained about the portfolio structure allows, for example, for increased engagement in profitable business areas. To establish such an integrated approach, high-quality and extensive data in all business areas is conducive (Al-Hakim, 2007; Kaplan et al., 1998). Enhanced hard-disk storage capacities (Walter, 2005) enable large-scale data collection and, thereby, the possibility of further data analyses for management support (Izenman, 2008). In conclusion, large-scale data mining has become an important task in financial risk governance that can open up further revenue streams (Yi and Gang, 2008). The logistic regression is currently the most used data-mining method in credit risk management, as most practitioners thereby score the financial viability of their customers. But other methods, such as decision trees, k-nearest neighbors, or support vector machines, are used for scoring purposes (Paleologo et al., 2010).

Due to the nature of credit analysis as a classification problem, cluster analysis can be used to examine the reliability and profitability of portfolios (Lacerda and Carvalho, 1999). Originally developed for biological classification (Saraçli et al., 2013) cluster analysis has gained attention, as enhanced computing power allows an effective use of this method (Blashfield, 1976). Kettenring (2006) shows that cluster analysis is increasingly used in different research areas ranging from archeology to zoology (Hill and Lewicki, 2006; Kettenring, 2008).

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Kettenring (2006) analyzes the applications of cluster analysis and finds that over 1,100 papers involving cluster analysis were published in 2003 from 646 in 1995 with an accelerating trend. Although mostly used in biology (e.g. Ferreira and Hitchcock, 2009; Kettenring, 2006; Sneth and Sokal, 1973), other areas of application can be found, for example, in marketing (Punj and Stewart, 1983); Sheth (1971) explores the "multivariate revolution in marketing-research". Moreover, Bacher et al. (2010) summarize possible applications within social science, and Blashfield (1976) as well as Hill and Lewicki (2006) show that cluster analysis is a common method used in psychology. Even recent inventions use cluster analysis to analyze texts, images, or multimedia data (Kettenring, 2008).

This wide range of applications is indicative of the advantages cluster analysis provides for credit portfolio management: Cluster analysis does not follow any distribution gained from sample data, and variables of different scale types can be used in the analysis (Mu and Zongfang, 2010), which is beneficial and necessary for complex credit portfolios. Therefore, information about the data structure and previously unnoticed relationships can be revealed, which supports efficient management (Ferreira and Hitchcock, 2009; Fraley and Raftery, 2002; Ward, 1963) and which makes cluster analysis a valuable tool for credit portfolio management. Therefore, the paper at hand provides a cluster analysis approach for credit portfolio management encountering both risk and return potential of credit contracts to optimize credit portfolios. The integrated consideration of risk and return figures can reveal clusters with high or, respectively, low profitability. This provides valuable insight for future portfolio management. Considering the aforementioned approach as an integrated classification method in credit portfolio management, we pose the following research questions:

1. *How is the performance of a credit portfolio improved through using a cluster analysis approach that considers the risk and return measures of the credit contracts?*
2. *What implications can be drawn for future credit management decision support if the underlying classification of a credit portfolio is known?*

By introducing a statistical method, so far only used in other disciplines or other applications, we hope and expect to improve credit portfolio analyses by a better data mining method than the widely distributed logistic regression. Furthermore, the integrated consideration of risk and return is anticipated to fulfill the needs for a deeper understanding of multidimensional data structures that are characteristic for credit portfolios. Consequently, future decision

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making in credit portfolio management may increase a company's profitability. By giving a concrete instruction on how to perform a cluster analyses of a credit portfolio and moreover suggesting recommendations for the settings of the cluster analyses, we expand existing credit portfolio literature. Consequently, financial intermediaries should be able to perform this sophisticated data mining technique without substantial effort.

The paper comprises six sections. After the introduction, a literature overview in section two covers the current research on cluster analysis in general and especially regarding credit management decision support. Section three introduces the integrated cluster analysis approach adjusted to the characteristics of credit portfolio management. In section four, multiple datasets of a financial institution are analyzed by using the suggested approach to identify further revenue potential. The fifth section summarizes the approach presented and addresses the practical and theoretical consequences. Finally, section six identifies limitation of the approach and future research potential.

III.1.2 Literature Overview

Sophisticated credit portfolio management is crucial for the value-based management of financial institutions, as credit portfolios yield both high risk as well as high return potential. The high risk of single credit contracts, basically arising from the possibility that counterparties may default, has been addressed through regulators requiring banks to keep capital for the risk of default (Hull, 2012). The Basel II accords led to the development of numerous internal rating models to estimate the probability of default as financial institutions are able to realize beneficial capital requirements (Henking et al., 2006; Hull, 2012). With the Basel III accords the common equity capital ratio norms tighten even more (Basel Committee on Banking Supervision, 2011) and therefore internal rating models have become more attractive for financial institutions.

The potential loss of a credit portfolio can, for example, be measured through a credit risk value at risk which is defined as the credit risk loss over a certain time that will not be exceeded with a certain confidence level. Hull (2012) states that banks calculate such a value at risk in order to determine the regulatory capital e.g. as provided by the Basel Accords and the economic capital (Basel Committee on Banking Supervision, 2011). However, the value at risk can also be used for active risk and portfolio management (Jorion, 2007) if the portfolio management uses the marginal or component value at risk of credit contracts in order to change the risk of the total portfolio.

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Even if the value at risk represents the return potential of credit contracts implicitly by the distribution function, a direct integration of the return potential is not given. In general, modern portfolio theory has not been easy to apply to credit contracts due to a number of problems such as the non-normality of loan returns and the unobservability of market-based loan returns (Saunders and Allen, 2002). Furthermore, that returns are often left undescribed and therefore models like CreditMetrics (J.P. Morgan, 1999) are not fully-fledged modern portfolio theory models. Therefore, financial risk-relevant features may commonly be measured by few key performance indicators, for example expected loss, value at risk, and exposure (Schönbucher, 2001).

Consequently, an integrated approach for analyzing credit portfolios with a focus on the actual costs and revenues of credit contracts is required in order to address the risk and return characteristics of credit contracts. Lahsasna et al. (2008) state that decision support systems are necessary for credit analysis, as they provide the essential speed for decision making and reduce the cost of credit analysis. Even if the logistic regression is the most common method for assessing credit risk, other techniques for the prediction of credit risk are increasingly important (Paleologo et al., 2010). Henking et al. (2006) list multiple methods which are used to build scoring models in order to estimate the probability of default, e.g. discriminate analysis, neuronal networks and regression models. Xiang and Yang (2011) summarize that more recently, classifying techniques are combined to make full use of every classifier for the credit scoring. Lahsasna et al. (2008), Mu and Zongfang (2010), as well as Paleologo et al. (2010), provide examples of more complex scoring models.

More complex models attempt to integrate default correlation into credit risk models because historical defaults tend to cluster (Schönbucher, 2001). Jaschke and Küchler (2001) state that there is room for new portfolio optimization methods based upon the coherent risk measures defined by Artzner et al. (1998) rather than value at risk or lower partial moments. Therefore, the set of widely used methods in practical credit management should be extended to include further methods. Thereby, the drawbacks of the logistic regression or other methods can be avoided by, for example, setting up multiple dependent variables, which is the basis for an integrated credit portfolio management approach that addresses not only risk but also costs and returns. Consequently, multivariate analytical methods can be used to create an integrated approach for a cost-return analysis of credit portfolios.

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In contrast to common regression models, a classification approach provides deep insight into the underlying structure of complex portfolios. As certain groups of similar credit contracts within the portfolio are not known in the beginning and are introduced only within the clustering process, a cluster analysis is suitable because it belongs to the methods of exploratory multivariate data analysis (Backhaus et al., 2011; Izenman, 2008; Sheth, 1971).

Today, cluster analysis is stated as one of the three most important multivariate analysis methods along with the principal component analysis and the discriminate analysis (Kettenring, 2006). In the field of finance, however, the online bank ING Direct used a modified cluster strategy after a regression analysis to identify the most profitable customers, which has attracted attention in *Forbes* magazine (Kettenring, 2006; Swibel, 2004). Xiang and Yang (2011) use cluster analysis to increase the prediction accuracy of credit risk and show that their model could improve credit risk management. Furthermore, Mu and Zongfang (2010) state that cluster analysis has been used since the 1990s in credit risk analysis to categorize credit grades. They introduce a new credit rating model for enterprises, which uses principal component analysis and cluster analysis to obtain optimal partitions of the comprehensive credit scores and, ultimately, determine the credit rating for the enterprises. Hu and Wang (2008) combine neural networks and cluster analysis to predict the default of the customers of a medicament enterprise. The paper at hand deviates from common methods in credit portfolio management by suggesting a new approach to identifying the profitability of customer clusters. The profitability of contracts is therefore determined by a return measure, calculated using the cash flow plan of the credit contract and a risk figure, including the expected cost of loss and the cost of risky capital of the contract.

Previous publications have used cluster analysis or other data-mining techniques to classify the risk of credit contracts and therefore assign probabilities of default and credit limits for customers. Within the paper at hand, the return component as well as the cost of credit contracts is integrated in the credit portfolio analysis, as this contains valuable possible optimization potential for further portfolio management. The analyzed real-world datasets provide a scale of this potential. To the best of our knowledge, there are yet no scientific papers addressing this research questions.

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III.1.3 Cluster Analysis Approach for Credit Portfolio Optimization

III.1.3.1 Selection of Clustering Method

Theodoridis and Koutroumbas (2009) state that clustering is used by humans every day to handle the huge quantities of information perceived; this happens via categorizing information into groups, or so-called clusters. In unsupervised learning, cluster analysis is a common tool for examination of multivariate datasets (Izenman, 2008) by assembling *n* objects into *k* homogeneous but ex ante unknown groups (e.g., Bacher et al., 2010; Backhaus et al., 2011; Saraçli et al., 2013). Furthermore, Sheth (1971) sets the objective that the groups or clusters are mutually exclusive and exhaustive. The concept of grouping objects into clusters is driven by a high degree of homogeneity within the clusters and dissimilarity between objects of different groups (e.g., Bacher et al., 2010; Backhaus et al., 2011; Leonhart, 2013). During the clustering, the number of groups, *k*, will be discovered, which is unknown at the beginning of this explorative clustering approach (Bacher et al., 2010; Izenmann, 2008). As the underlying cluster structure of a credit portfolio is unknown, this explorative approach is suitable. In contrast to principal component analysis, cluster analysis is not a straightforward process because a rigorous and automated way to find cluster structures within complex data does not exist. Therefore, it is important to practice cluster analysis effectively (Fraley and Raftery, 2002; Kettenring, 2006).

Multiple clustering methods can be used for an explorative cluster analysis approach (Bacher et al., 2010). A hierarchy, consisting of a tree of clusterings (Theodoridis and Koutroumbas, 2009), is beneficial for the interpretation and is generated through hierarchical cluster methods (Cormack, 1971). Ward's method (1963), as a hierarchical method designed to generate clusters with a minimal variance within the clusters (Blashfield, 1976; Hill and Lewicki, 2006), is often used in practical applications of cluster analysis (Backhaus et al., 2011; Fraley and Raftery, 2002). Different studies in the literature conclude that in general Ward's method is an adequate, or the best, choice for practical application (Saraçli et al., 2013); see, for example, Milligan (1980), Milligan and Cooper (1988), and Ferreira and Hitchcock (2009). This remains true despite that Ward's method seems to lose performance when the data contains a substantial amount of outliers (Liu et al., 2010; Milligan, 1980; Saraçli et al., 2013). As the clusters are represented by a centroid, they are well interpretable (Leonhart, 2013). Due to these benefits, the paper at hand suggests using this method for the cluster analysis of credit portfolios.

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The measure of proximity used by the clustering method expresses the distances between the data records and, therefore, provides an indication of the similarity or dissimilarity of the objects (Saraçli et al., 2013). Bacher et al. (2010) and Bahrenberg et al. (2008) claim that Ward's method requires the use of the squared Euclidean distance as a proximity measure, as the within-cluster variance is attributable to the squared distances of the associated objects (Bahrenberg et al., 2008).

The paper at hand introduces an integrated credit portfolio management approach that considers risk and return simultaneously. Therefore, cost and return figures are identified as so-called target variables of the cluster analysis. After the data standardization, all included variables are comparable, and, therefore, an undesired weighting is excluded. If the target variables dominate the remaining variables in terms of the scale of their entries, then their influence during the cluster process will increase. Moreover, a conscious weighting of the target variables can produce this domination. However, weighting has to be done with great care, as otherwise it only leads to less effective clusterings (Gnanadesikan et al., 1995). Nevertheless, the results should be compared to a non-weighting clustering solution to create deeper understanding of the dataset.

III.1.3.2 Appropriate Selection of a Cluster Solution

After the clustering using Ward's method, the evaluation of the results can be done. The number of clusters has to be determined based on the hierarchy of clusterings (Backhaus et al., 2011). Backhaus et al. (2011), Milligan and Cooper (1985), and Sneath and Sokal (1973) describe the decision on the number of clusters as a conflict between the requirements of homogeneity and the manageability of the cluster solution. This conflict occurs because larger clusters, comprising a smaller number of clusters, lead to higher heterogeneity within the clusters and vice versa. Milligan and Cooper (1985) compare internal quality indices that can be applied to select an appropriate number of clusters from a given hierarchy. The stopping rule of Calinski and Harabasz (1974) is among the best of the tested criteria (Milligan and Cooper, 1985) and is suggested for determining the optimal cluster number (Backhaus et al., 2011). Calinski and Harabasz (1974) define the index by:

$$VRC = \frac{\operatorname{trace} B_k/(k-1)}{\operatorname{trace} W_k\,/(n-k)} \tag{1}$$

where $X = \{x_{ij}\}$ is the $n \times m$-data matrix, with n objects (e.g., credit contracts), m variabels, and the number of clusters k. Furthermore, the trace of a matrix x is defined as the sum of all

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the main diagonal elements, i.e., $trace\ X = \sum_{i=1}^{n} x_{ii}$. Thereby, the within-group dispersion matrix for the data that is clustered into k clusters is defined as

$$W_k = \sum_{r=1}^{k} \sum_{i \in C_r} (x_{ri} - \bar{x}_r)(x_{ri} - \bar{x}_r)^T \tag{2}$$

and the between group dispersion matrix for the data that is clustered into k clusters is defined as

$$B_k = \sum_{r=1}^{k} n_r (\bar{x}_r - \bar{x})(\bar{x}_r - \bar{x})^T \tag{3}$$

where $\bar{x}_r$ is the centroid or medoid of cluster r, $\bar{x}$ is the centroid or medoid of the whole data matrix, C_r represents the indices of objects in cluster r, and n_r the number of objects in cluster r (Calinski and Harabasz, 1974; Walesiak and Dudek, 2014). By using this internal quality index, the number of clusters to be considered can be chosen. Furthermore, the index can be used to compare different clustering solutions in general (Walesia and Dudek, 2014) to find the best clustering solution out of a pool of applicable methods.

In conclusion, the introduced approach seeks to overcome the challenges that credit portfolio managers face when applying a cluster analysis on a given portfolio to gain further insight. Before a cluster analysis can be performed, certain data transformations are necessary. After creating a standardized database, the genuine cluster analysis may be carried out using Ward's method. The introduced weighting approach helps to increase the relevance of the analysis for management decisions and enables the applicant to select certain target variables. The following section will show how the analysis is carried out, which insight can be gained, and which further challenges the applicant may face when performing the analysis. For the technical implementation, the software *R* (R Core Team, 2012) provides several packages that implement Ward's method using mostly squared Euclidean distances, where the fastest implementation can be found in *fastcluster* (Müllner, 2013). A variety of different algorithms, proximity measures, standardizations, and other features is provided by the *clusterSim* package (Walesiak and Dudek, 2014), which yields an implementation of different algorithms for comparative purposes.

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III.1.4 Evaluation of the Approach on Sample Real-World Datasets

III.1.4.1 Sample Portfolio Introduction

The evaluation of the approach will be done using three real-world data samples provided by a financial services institution that has to remain anonymous due to reasons of competitiveness. The datasets have the following properties:

Dataset A is a developed portfolio containing 7,853 contracts and 21 variables.

Dataset B is also a developed portfolio, but it has a different underlying distribution structure containing 14,313 contracts and 22 variables.

Dataset C represents an emerging portfolio with 1,825 contracts and 25 variables.

Because large numbers of variables make it impossible to perform a cluster analysis, having, at best, the complexity $O(n^2)$ (Müllner, 2013) and lead to an over- or underrepresentation of certain factors, variable selection is necessary. Gnanadesikan et al. (1995) suggest two approaches for the selection of variables: selecting variables using assigned weights or directly selecting a subset of the initial variables. An integrated approach to the variable selection is favorable in practical applications in credit portfolio management because low-quality data can easily be excluded, and statistical analyses will provide further guidelines for the variable selection. Therefore, an extensive selection process is applied using statistical measures, like the number of missing entries, as well as interviews with the portfolio managers in order to identify the relevant variables.

Table 1 shows the variables that have been selected for the analysis along with a brief description and the data type. However, the three datasets differ significantly among themselves. For example, the data availability in the datasets is different for the variable *rating migration* due to the data quality of the underlying variables.

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Table 1: Variables available in the datasets A, B, and C

variable name	brief description	availability in dataset	data type	scale for dataset A
contract number	ID Variable	A, B, C	indexing	A-1 to A-7853
trust	ID Variable	A, B, C	indexing	1 to4817
counterparty	ID Variable	A, B, C	indexing	ID
initial purchase price	initial price of leased object	A, B, C	continuous	2,074 to 25,000,000
equipment collateral value	collateral value	A, B, C	continuous	0 to 5,886,066
equipment collateral value end of term	collateral value at the end of term	C	continuous	-
outstanding	exposure value	A, B, C	continuous	2,002 to 18,188,944
amount at risk	exposure value	A, B, C	continuous	2,002 to 18,188,945
outflow	exposure value	A, B, C	continuous	2,074 to 25,000,000
cost rate	cost figure of contract	A, B, C	continuous	0.01 to 0.69
customer rate	return figure of contract	A, B, C	continuous	0.00 to 6.67
profit margin	profit figure of contract	A, B, C	continuous	-0.58 to 6.62
mapped rating	rating of the trust or counterparty	A, B, C	ordinal	1.0 to 9.0
rating migration	magintude of rating change (compared to contract start)	B, C	ordinal	-
guarantor	indicates the availability of a guarantor	B, C	indicator	-
maturity	days to maturity	A, B, C	continuous	180 to 5,509
contract start month	start date of contract	A, B, C	continuous	1 to 12
contract start year	start date of contract	A, B, C	continuous	2003 to 2013
contract end year	end date of contract	A, B, C	continuous	2013 to 2026

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IFRS contract credit type	contrat type	A, B, C	nominal	operate lease; sales type lease; direct finance lease
contract currency	contract currency	C	nominal	e.g. EUR, USD
distribution channel	point of sale	A, B, C*	nominal	e.g. flow
business segment	type of business	A, C	nominal	direct finance; vendor finance referred; vendor finance sales aid
business category	category of business indication the relation to the financial institution	A, B, C	nominal	1 - 4
counterparty business	business segment of counterparty (ISIC)	A, B, C*	nominal	e.g. argiculture & forestry, finance

* different entry structure

Thereby, the customer rate is calculated by contract number using the cash flow plan of the credit contract, and the cost rate reflects the rate of funds, the expected cost of loss, and the cost of risky capital of this contract. Furthermore, the profit margin represents the difference between the customer rate and cost rate.

III.1.4.2 Data Transformations

Variables in a credit portfolio management data warehouse are not comparable, as they are usually measured on different scales, have different data types, or are hierarchically dependent, leading to an under- or overrepresentation of certain factors (Bacher et al., 2010). To use the Euclidean distance, all variables need to have an interval data type because the calculation of this distance for nominal scaled variables is not possible. Therefore, the nominal scaled variables are transformed into indicator variables, resolving the nominal variables: one is applied if the variable has the indicated entry, and zero is applied otherwise (Bacher et al., 2010; Backhaus et al., 2011). Even if most of the variables in the considered datasets already have a suitable data type (i.e., they are of interval, indicator, or ordinal type), the nominal variables *IFRS contract credit type, distribution channel, business segment, business category, and counterparty business* need to be transformed into indicator variables.

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Furthermore, it is appropriate to exclude missing values from the analysis, as Kaufman (1985) confirms that treating missing values has a minimal effect on the cluster analysis.

A correlation analysis using Pearson's correlation coefficient is done within every dataset because high correlations lead to overrepresentation of certain factors in the cluster analysis. High correlations of over 90% have been discovered, especially among the variables *initial purchase price, equipment collateral value, outstanding, amount at risk,* and *outflow* (all of them referring to the volume of the credit agreement). Furthermore, we observed a high correlation between the two variables *customer rate* and *profit margin* (both referring to the profitability of the credit agreement). To avoid the overweighting of certain factors, the following variables are excluded because of high correlations to *initial purchase price* respectively *customer rate*:

Dataset A *Outstanding, amount at risk, outflow,* and *profit margin*

Dataset B *Equipment collateral value, outstanding, amount at risk,* and *outflow*

Dataset C *Outstanding, amount at risk, outflow,* and *profit margin*

The two variables *initial purchase price* and *customer rate* thereby cover most of the highly correlated information from the excluded variables. As a result, some further information exceeding the correlation inevitably gets lost. Whether this sparse information is likely to provide some additional information in order to improve clustering is due to further research. However, this analysis would be very extensive as a huge variety of possible variable combinations have to be arranged, analyzed and evaluated. After the stated analyses and exclusions, the datasets A and C consist of the 35 variables and the dataset B of 36 variables with acceptable correlation.

As stated before, Ward's method loses performance in the presence of extreme variable values, or so-called outliers. In the paper at hand, the outliers are defined as entries lying outside a range of six times the standard deviation in a positive or negative direction centered by the mean of the continuous variables. The number of contracts having these extreme values is 143 in dataset A, 87 in dataset B, and 32 in dataset C. As the performance of the clustering algorithms decreases in the presence of outlying objects, these few contracts have to be removed before the clustering is done and then analyzed separately in a later step.

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III.1.4.3 Clustering Settings

To verify the introduced approach using Ward's method with the squared Euclidean distance, we simulate several cluster analyses of the real-world datasets. Thereby, several different clustering methods, proximity measures, and two different standardization methods are compared on the basis of their Calinski-Harabasz index, instead of conducting just one cluster analysis and run the risk of choosing a suboptimal analysis specification. Therefore, 1,624 different cluster solutions of the real-world datasets generated by the following multiple settings are considered:

• Possible cluster numbers	2–30
• Standardizations	z-standardization, unitization
• Proximity measure with corresponding clustering methods	Manhattan, Euclidean, Chebyschev, GDM1 single, complete, average linkage, McQuitty, k-medoids
• Proximity measure with corresponding clustering methods	Squared Euclidean single, complete, average linkage, McQuitty's method, k-medoids, Ward's methods, centroid, median

The clustering methods single linkage and median are outperformed in both datasets by other methods. The best-performing methods in both datasets are average linkage, McQuitty's method (1960), k-medoids, and Ward's method. Cluster solutions with a low number of clusters seem to be preferred by the Calinski-Harabasz index, as shown in Table 2, but a cluster solution with more than two clusters is recommended due to the difficulties of interpretation of a two-cluster solution in a dataset containing more than 7,000 credit contracts. The results show that cluster solutions with more than nine clusters found by Ward's method yield the highest Calinski-Harabasz index. Therefore, Ward's method seems to be an appropriate choice when a large number of clusters is desirable, as it is reasonable in portfolios with several thousand credit contracts. Small cluster numbers will not provide the sufficient in-depth insight necessary for future portfolio management. Furthermore, the squared Euclidean proximity measure performs best in dataset C and second best in dataset A. As

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Ward's method is favorable for applications in credit portfolio management due to the desired higher number of clusters, the squared Euclidean proximity measure is used.

Table 2: Results of simulations

	dataset A		dataset C	
proximity measure	C-H index	rank	C-H index	rank
Manhattan	2353,6	2	418,5	4
Euclidean	2353,1	3	390,6	11
Chebyschev	968,9	196	156,5	398
GDM1	2348,6	6	483,3	1
Squared Euclidean	2355,4	1	479,8	2
number of clusters				
2-9	2355,4	1	483,3	1
10-19	1341,1	62	332,6	40
20-29	1124,3	116	265,6	103
clustering method				
single	315,8	851	78,4	888
complete	2317,6	7	327,9	41
average	2353,6	2	483,3	1
mcquitty	2353,1	5	403,8	9
pam	2062,2	11	470,1	3
ward	2306,1	9	479,8	2
centroid	2355,4	1	69,1	988
median	316,5	850	103,9	748

Due to the different scale levels of the variables (i.e., indicator variables having levels 0 and 1, and the exposure having levels from 0 to several million), the variables need to be transformed into an equal scale to ensure comparability. Otherwise, the variables with the widest numerical range will dominate the other variables in terms of squared Euclidean

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distance. To find the best standardization method, a simulation based on the real-world data comparing different methods is conducted. Walesiak and Dudek (2014) provide multiple standardization methods for addressing different data structures. For the evaluation of different standardization methods, 116 (= 29×4) simulations are done with the following standardization methods:

Z-standardization

$$z_{gi} = \frac{x_{gi} - \overline{x_i}}{s_i} \tag{4}$$

Unitization

$$z_{gi} = \frac{x_{gi} - \bar{x}_i}{\max_g x_{gi} - \min_g x_{gi}} \tag{5}$$

Unitization with zero minimum

$$z_{gi} = \frac{x_{gi} - \min_g x_{gi}}{\max_g x_{gi} - \min_g x_{gi}} \tag{6}$$

Normalization in range [−1, 1]

$$z_{gi} = \frac{x_{gi} - \bar{x}_i}{\max_g |x_{gi} - \bar{x}_i|} \tag{7}$$

Where z_{gi} denotes the standardized value of the object g in the standardized variable Z_i, the value of object g in the not-standardized variable X_i is denoted by x_{gi}, and the mean of the variable X_i by $\overline{x_i}$. The standard deviation of the values of the variable X_i is s_i. All simulations for the three real-world datasets are done using Ward's method with the squared Euclidean distance with cluster numbers from 2 to 30 and are evaluated with the Calinski-Harabasz index. The results of the simulation show that the z-standardization performs worst in the three datasets, as shown in Table 3. The best-performing standardization for smaller and higher numbers of clusters is the normalization in range [−1, 1], which is therefore used in the following simulations.

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Table 3: Results of simulations with respect to standardizations

standardization	dataset A		dataset B		dataset C	
	C-H index	rank	C-H index	rank	C-H index	rank
z-standardisation	834.6	88	1235.1	88	205.0	88
unitization	2306.1	7	4764.7	6	479.8	3
unitization with zero minimum	2306.1	8	4764.7	7	479.8	4
normalization in range [-1,1]	3924.4	1	8398.7	1	665.9	1

III.1.4.4 Clustering

The classification of the datasets using the stated standardization method and proximity measure provides a first indication of the clusters existing in the datasets. However, the settings favor small numbers of clusters, which complicates the interpretation of the results. Therefore, a modified clustering procedure that allows stronger interpretations due to the higher number of clusters is desirable. As the cost rate and customer rate reflect the risk and the return figures in the given datasets, these variables are chosen as target variables. To categorize the credit contracts under the risk and return profile, the two target variables *cost rate* and *customer rate* will be assigned a higher weight, because the *customer rate* reflects the return as calculated in the cash flow plan of the contract and the *cost rate* reflects risk as included in the rate of funds, the expected cost of loss, and the cost of risky capital of the credit contract.

A simulation is done where weights from 0 to 10,000 in real-world datasets A and B or 0 to 100,000 in real-world dataset C are assigned for the target variables with a step size of 100. The results show improvement of the Calinski-Harabasz index and are compared to the solutions without any weighting. A cluster number of over 50 is considered not suitable, as such a breakdown leads to very small clusters with low importance in the portfolio context. The following table illustrates the optimal weights for each portfolio with their respective Calinski-Harabasz index being compared to the unweighted result.

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Table 4: Simulations of the assigned weights for the customer rate and cost rate

	weighting factors		description	optimal C-H index	optimal cluster number
data-set	simulation range	step size			
A	[0,0]	-	solution without any weighting	3924,42	2
	[0,10000]	100	local optimum found at weights 4700, but other possible solutions might be discovered using weights in the ranges [0,1000], [3000,3200], [4600,4800] and [5800,6200]	13172,01	47
	[0,1000]	1	local optimum at weights 965	12897,37	21
	[3000,3200]	1	local optimum at weights 3101	12916,46	47
	[4600,4800]	1	local optimum at weights 4762	13255,74	47
	[5800,6200]	1	local optimum at weights 6009	12829,29	23
B	[0,0]	-	solution without any weighting	8398,78	2
	[0,10000]	100	optimum at small weights lying in the range [0,100], starting from weights of 500 or higher the Calinski-Harabasz statistic fluctuates in a small range around 7400	8398,78	2
	[0,100]	1	optimum at weights of 0	8398,78	2
C	[0,0]	-	solution without any weighting	665,97	2
	[0,100000]	100	optimum at small weights in the range [0,2600], starting from weights of 2600 the Calinski-Harabasz statistic decreases to a value just under 2707		
	[0,2600]	1	local optimum found at weights of 328, where the cluster number in the cluster solution drops from over 50 in the neighboring weights to 47	2741,91	47

The results from dataset A show that high weighting leads to an increasing Calinski-Harabasz index and, therefore, to a better cluster solution. Nevertheless, the optimal cluster number mostly exceeds the threshold of 50. The ranges where lower cluster numbers occur are analyzed in more detail to find some local optima. Thereby, the optimum is found at weights of 4,762 with 47 clusters.

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Dataset B shows high Calinski-Harabasz indices with low weightings that decrease rapidly and stabilize at a level of approximately 7,400. The optimal weight can be found with weighting factor zero, where the Calinski-Harabasz index is 8,508.08, representing a two-cluster solution. This means that excluding the target variables leads to better cluster solutions. However, as the target variables are essential for the portfolio management, a direct exclusion does not seem appropriate; instead, an interpretable cluster solution containing both target variables should be achieved.

In dataset C, high Calinski-Harabasz indices occur at weights up to 2,600. In this case, the maximal number of cluster, 50, will be chosen by any solution with higher weightings. The weighting optimum is found at weights of 328 with a 47-cluster solution.

To gain deeper insight into these findings, the optimal solution from dataset A will be described in more detail. With the 2,600 times cost and customer rate weighting, two cluster solutions show local maxima: the 47- and the 19-cluster solution. For reasons of clarity, the 19-cluster solution is preferred for this matter. A precise analysis of the cluster shows that especially the contracts with very high or very low customer and cost rates are assorted in a few clusters. However, the cluster solution without weighting, no matter whether a 5- or 19-cluster solution is selected, shows a broad distribution of customer and cost rates in each cluster. Figure 1 illustrates this distribution.

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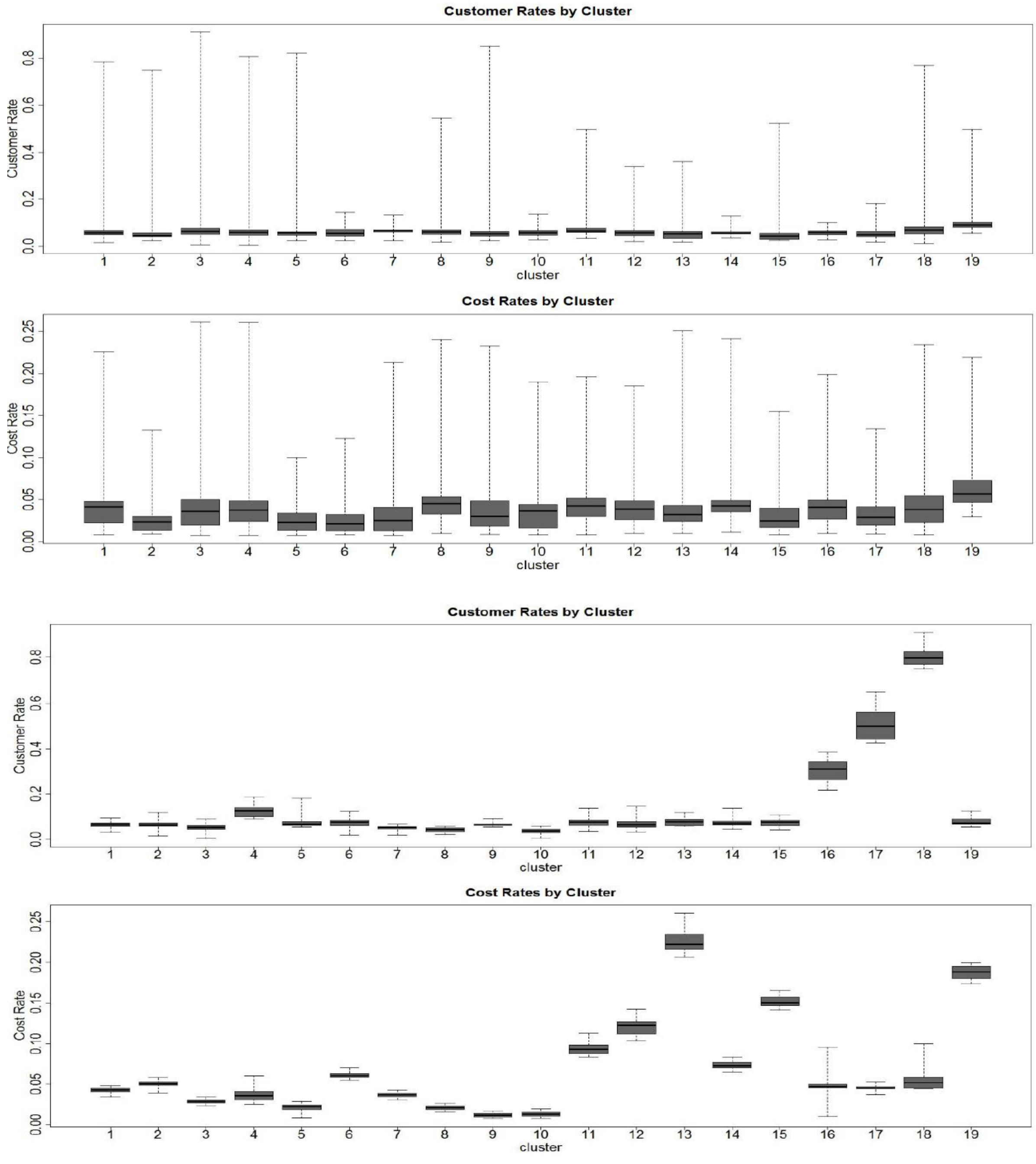
Figure 1: Distribution of customer and cost rate in the unweighted (above) and weighted (below) 19 cluster solutions of dataset A



A further breakdown in ISIC codes of the clusters having this significant high or low margin provides exactly the valuable information that is beneficial for future portfolio management, as these more extreme rates obviously occur only in certain ISIC codes.

In summary, it can be recognized that a cluster analysis in credit portfolio management can be a useful instrument to detect further revenue streams. Without the cluster analysis, the optimization potential in the datasets would not have been discovered. The paper at hand aims

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to provide a method set that can be used for cluster analyses in a credit portfolio management setting. The critical issues are addressed throughout the paper to provide suitable solutions for practitioners. As shown with dataset A, a weighting approach in the cluster analysis can lead to better insight into the structures of the data. This is especially the case if certain target variables are to be analyzed. A weighting approach can lead to deeper insight into the underlying cluster structure when carried out properly. Nevertheless, a weighting approach should be justified with simulations to find appropriate weights.

III.1.5 Conclusion and Consequences

When credit portfolio data is not analyzed in detail with great care, valuable profitability potential in the portfolio management could be lost. The introduced integrated approach presented, considering the risk and return of credit contracts, leads to further information which is targeted for the profitability of credit portfolios and which provides decision support for the management. As shown throughout the paper at hand, a cluster analysis of the underlying credit portfolio can provide great insight into the underlying cluster structure. As a consequence of the additional information gained through cluster analyses, future growth areas as well as rather unprofitable ones could be identified. Moreover, the analysis will lead to further insight into the portfolio structure, as similar groups of credit contracts could be identified. Thus, unprofitable groups of credit contracts or these contracts with an inappropriate risk could be restructured in order to improve the credit portfolio. After revealing the cluster structure, further analyses can be carried out and the gained information can be used in future price negotiations and sales target agreements. Thus, detailed information about future credit contracts could be deduced by predicting the classification of a credit transaction based on the patterns within the existing portfolio. This information is beneficial for decision making in credit portfolio management for example by increasing the sales volume in certain profitable business areas or reducing existing exposures in areas lacking profitability. Consequently, the financial intermediary or any other institution controlling a credit portfolio may be able to increase profit and gain competitive advantages from intelligent data analytics.

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III.1.6 Limitations, and Outlook

With regard to the limitations of the suggested approach, we have to mention that data selection cannot be fully automated; the necessary transformations need to be performed manually. Therefore, a cluster analysis of an existing credit portfolio is time consuming and has to be performed with great care. Even if the suggested approach provides certain guidelines, the results need to be approved for use in management support, as the cluster analysis only reveals the underlying structure. Moreover, the optimal methods might be slightly different depending on the portfolio analyzed. To carry out a meaningful cluster analysis or any other data-mining method, a variable selection, standardization, or weighting leads to manual impacts on the analysis. It is especially challenging to select an optimal weighting because the number of clusters needs to be selected simultaneously. We suggest that further research should aim to create an integrated approach for selecting appropriate weights and cluster numbers simultaneously under the paradigm of interpretability. Furthermore, the variable selection for cluster analysis, especially the elimination of highly correlated variables, could be examined in further research. Moreover, a sensitivity analysis examining the robustness of the found cluster solutions could be a subject for further research. The results of the cluster analysis should be validated in the portfolio context to determine sophisticated relations between the contracts and contract variables. Nevertheless, the suggested approach has already led to promising insights into analyzing credit portfolio data by applying a new method and giving advices on how to perform a credit portfolio cluster analysis.

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IV Decision Support in Corporate Hedging Considering Earnings Volatility

IV.1 Research Paper 5: "Toward an Optimal Hedging Strategy Considering Earnings Volatility Through Fair Value Accounted Financial Derivatives"

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Structured Abstract:

Purpose

The discussion on the adoption of fair value accounting in the financial industry has been rather controversial in recent years. Under this accounting regime, the change in market values of specific assets must be considered as profit or loss. Critics argue that fair value accounting induces higher earnings volatility compared to historical cost accounting and, therefore, may initiate a downward spiral during recessions. Thus, increased earnings volatility induces costs, which can be explained by disappointed capital market expectations. Consequently, in general a lowering of earnings volatility will be rewarded. Consistent with this theoretical finding, empirical research provides strong evidence that companies pursue income smoothing in order to reduce earnings volatility. In contrast to industrial corporations, financial institutions may easily reduce their earnings volatility by engaging in

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additional hedging activities. However, more intense hedging usually reduces expected profits.

Design/methodology/approach

Based on a research project initiated by a large German bank, this study quantitatively models the trade-off between the (utility of) costs of earnings volatility and the reduction of profit potential through additional hedging.

Findings

By conducting sensitivity analyses and simulations of the crucial factors of the trade-off, we examine relevant causal relationships in order to obtain first indications about the economic benefits of income smoothing.

Originality/value

To the best of our knowledge, we are the first to develop an optimization model that supports decision-making by attempting to determine an optimal (additional) hedging degree considering the costs induced by earnings volatility.

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IV.1.1 Introduction

Following the adoption of fair value accounting in financial reporting, companies are required to consider derivative financial instruments on their balance sheets at fair value. Any changes in the market value of derivative instruments would directly affect a company's reported earnings. In contrast to historical cost accounting, this accounting practice especially leads to a sharp rise in the earnings volatility of financial institutions holding large derivatives portfolios (Barth et al. 1995; Hodder et al. 2006; Duh et al. 2012). Therefore, critics state that fair value accounting could initiate a downward spiral during recessions because banks would be unwilling to sell securities at prices that would force them to mark down other assets (Laux and Leuz 2009). On the other hand, advocates argue that fair value accounting, as regulated by the Statement of Financial Accounting Standards (SFAS) No. 133, SFAS No. 157, and the International Accounting Standard (IAS) 39, improves transparency related to the valuation of financial assets (Laux and Leuz 2009; Heaton 2010). Further, the extant scientific literature reports that fair value accounting increases the relevance of earnings volatility for financial institutions, as it captures significant elements of risk priced by the market (Beaver et al. 1970; Hodder et al. 2006). Thus, higher earnings volatility increases the costs of capital. Consequently, earnings volatility should be taken into account when managing a portfolio of derivatives in order to avoid negative market reactions. Therefore, banks may be inclined to smooth their earnings volatility, e.g. by engaging in hedging activities. In contrast, the reduction of earnings volatility can also be associated with *earnings management*, which includes, for example, using accruals to shift economic earnings between accounting periods. However, in this paper we neglect this form of earnings management and solely focus on reducing earnings volatility by offsetting derivative positions that are accounted at fair value.

From an investor's perspective, the balance sheet in general and the disclosure of earnings in particular are the primary sources of company-specific information (Liu et al. 2002) and the anchor for value in the Ohlson (1995) valuation framework. Since earnings are thought to be unpredictable and risky (Graham et al. 2005), providing reliable and precise information about earnings could reduce the investors' *information risk*, which reflects "the ability of investors to ascertain the valuation parameters underlying a particular asset" (Riedl and Serafeim 2011). According to classical asset pricing models, the existence of information risk leads to higher cost of capital (Lambert et al. 2007). Since earnings volatility is a possible source of information risk, several empirical studies report a strong dependency between non-volatile

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(i.e., smooth) earnings and lower cost of capital (Michelson et al. 1995; Subramanyam 1996; Francis et al. 2004; Rountree et al. 2008).

Further, Ronen and Sadan (1981) as well as Tucker and Zarowin (2006) state that managers convey private information about their company's future performance by smoothing earnings, thereby mitigating information asymmetries in favor of their investors. Similarly, Graham et al. (2005) assert that the vast majority of chief financial officers (CFOs) prefer to smooth earnings. Consequently, our investigation is motivated by the disadvantages of earnings volatility in general, and the earnings volatility induced by fair valued derivatives in particular.

Financial institutions can reduce the fair value fluctuations of financial derivatives by engaging in additional hedging activities.[1] However, hedging reduces the expected return of the derivatives portfolio. Thus, engaging in additional hedging activities to smooth earnings leads to a trade-off between the costs of earnings volatility and a reduction in expected profit. Based on an existing portfolio and simulated data, we develop an optimization model that determines the optimal hedging strategy.

In this study, we examine the following research questions:

Research Question 1: What is the connection between earnings volatility and cost of capital?

Research Question 2: How can the utility of reduced earnings volatility be quantified?

Research Question 3: What is the optimal additional hedging strategy considering both the expected return of a derivative transaction and the utility associated with the costs of (remaining) earnings volatility?

Research Question 4: How does a company's sensitivity toward earnings volatility (reduction) influence the optimal (additional) hedging strategy?

By addressing these research questions, we attempt to contribute to the extant literature in the following ways. First, to the best of our knowledge, this is the first study to introduce a (prototypical) utility function that evaluates and quantifies the earnings volatility in the income statement. This research is a first step toward an optimal hedging strategy that considers cost of capital related to earnings volatility. Moreover, we attempt to provide initial

[1] We assume that the bank uses a perfect hedge.

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guidelines for considering earnings volatility in a derivatives portfolio. We assume the cash flow volatility of the derivative has already been hedged according to the company's optimal conditions with respect to its risk-return profile. Accordingly, we analyze an additional hedging degree that accounts for costly earnings volatility induced exclusively by cash flow volatility. In sum, we attempt to contribute to practice by establishing guidelines for bank managers on how to manage the cost of earnings volatility.

The remainder of this paper is organized as follows. In Section 2, we review the extant research on fair value accounting in income statements, earnings volatility, and the corresponding costs. Subsequently, Section 3 describes the research methodology of this study and the basic model setting, including its assumptions. This is followed by a description of our dataset, a prototypical application of our model, and a sensitivity analysis in Section 4. The conclusions and the contributions to literature and practice are discussed in Section 5. The final Section 6 presents the limitations of our optimization model and directions for further research.

IV.1.2 Literature Review

IV.1.2.1 Fair Value Accounting and Its Effects on Earnings Volatility

The fair value of a derivative is determined by the present value of its expected future cash flows. Consequently, variations in the future expectations change the fair value of the financial derivative. As the balance sheets of financial institutions almost entirely consist of financial instruments, the banking industry is at the center of the controversy about the usefulness of fair value-based income measures. The introduction of IAS 39 and SFAS No. 157 in the U.S. substantially affected financial institutions, as many of their financial instruments now have to be reported at fair value. As defined by the International Financial Reporting Standards (IFRS) 13, fair value is “the price that would be received to sell an asset or paid to transfer a liability in an orderly transaction between market participants at the measurement date.” The advocates of fair value accounting believe that mark-to-market accounting provides more relevant and up-to-date information to the stakeholders of a firm (e.g., Lauz and Leux 2009; Heaton 2010). For instance, Barth (1994) observes that the fair value estimates of investment securities are reflected in the share prices of banks. Moreover, Barth et al. (1996) and Eccher et al. (1996) conclude that the SFAS No. 107 fair value estimates of securities and loans are

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value relevant.[2] Additionally, Hodder et al. (2006) provide evidence that fair value accounting captures the market-based risk factors in a superior manner. However, the critics of fair value accounting highlight its complexity and the inherent use of judgment. With the adoption of fair value accounting, earnings volatility distinctly increases; this is documented extensively in prior studies. For example, Barth et al. (1995) find that the earnings of banks when considering the fair value estimates of investment securities are significantly more volatile than those when using historical cost accounting. Similarly, Beatty et al. (1996) show that switching to fair value accounting increases the volatility of non-derivative investments. Moreover, Duh et al. (2012) conclude that the volatility of both net income and comprehensive income increases after applying fair value accounting to financial instruments.

IV.1.2.2 Income Smoothing

In order to avoid volatile earnings and to circumvent the reporting of such volatility to investors, income smoothing has proved to be an effective measure. In general, income smoothing occurs when the variability of reported earnings is reduced (Goel and Thakor 2003). The evidence for income smoothing is manifold (Subramanyam 1996; Graham et al. 2005; Rountree et al. 2008). Several prior studies have reported that financial institutions apply income smoothing in order to reduce earnings volatility (Fudenberg and Tirole 1995; Kanagaretnam et al. 2003). For a thorough analysis, income smoothing can be categorized as normal or intentional smoothing. *Normal smoothing* means that the business model itself generates an inherent, smooth income stream (Eckel 1981). In contrast, *intentional smoothing* is characterized by conscious earnings management and can be classified into artificial smoothing and real smoothing.

Artificial smoothing entails a deliberate effort to artificially reduce the variability of the income stream (Imhoff 1981). Accounting discretion about accruals is used to reduce the intertemporal variability of reported earnings and to conceal a firm's real economic performance (Ronen and Sadan 1981). Earnings management via artificial smoothing is predominantly achieved by exploiting the flexibility in the reporting standards. However, it is important to note that unlike real smoothing, artificial smoothing does not affect cash flows.

Real smoothing involves management decisions to (re-)structure revenue-generating events in such a way that they produce a smooth income stream (Albrecht and Richardson 1990;

[2] Eccher et al. (1996) mean "value relevance in terms of the association of supplementary fair value disclosures with share prices."

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Lapointe-Antunes et al. 2006). Such decisions directly affect cash flows and are not achieved via accruals management. In contrast to *normal smoothing*, in the case of real smoothing, business activities are adjusted on purpose in order to generate a low level of earnings volatility.

Some recent studies suggest that firms manipulate business activities to manage earnings (Graham et al. 2005; Roychowdhury 2006). However, recent work also suggests that only real smoothing affects the stock market valuation. For instance, Rountree et al.'s (2008) findings indicate that the market values hedging activities positively only when they directly influence cash flow volatility. The authors claim that income smoothing via accruals (i.e. earnings management) is not value enhancing. Further, Wang (2014) suggests that institutional investors in particular "see through" earnings smoothed via discretionary accruals (i.e., they anticipate artificial smoothing) and do not attach value to them. Given these insights, our optimization model will focus on real smoothing to reduce earnings volatility.

IV.1.2.3 Empirical Dependency between Earnings Volatility and Cost of Capital

In addition to the literature on income smoothing, many empirical studies and theoretical work support the proposition that an increased and higher quality of disclosure reduces a company's cost of capital (Botosan 1997; Leuz and Verrecchia 2000; Botosan and Plumlee 2002). Several empirical studies have examined the impact of earnings volatility - as a central information of disclosure - on the costs of capital. Beaver et al. (1970) were among the first to document the risk relevance of earnings volatility by showing that earnings volatility has a high contemporaneous association with the market-model beta. By influencing the capital asset pricing model (CAPM) beta, high earnings volatility increases the riskiness of a security, thereby raising the cost of capital. Lev and Kunitzky (1974) provide evidence that the extent of income smoothing is related to the overall risk (standard deviation of periodic stock returns) and the systematic risk beta. Hodder et al. (2006) support the finding that volatility in full-fair value income reflects the effects of risk factors that are not completely captured by volatility in net income or comprehensive income. They show that volatility is positively related to the required rate of return on equity capital. Thus, income volatility is an element of risk that increases expected returns and decreases share prices.

However, Bao and Bao (2004) argue that although the variability of earnings is smaller, smoothers' earnings quality is not guaranteed and should be considered simultaneously. The most direct empirical evidence for the dependency between cost of capital and earnings

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smoothness is provided by Francis et al. (2004). They examine seven accounting attributes, one of which is earnings smoothness, and identify a negative relation between earnings smoothness and cost of capital. McInnis (2010) is one of the few researchers who provides evidence that is inconsistent with the conclusion that income smoothing could lead to a lower cost of capital.[3] Nevertheless, the consensus in the extant empirical literature is that there is a positive correlation between earnings volatility and cost of capital.

IV.1.2.4 Theoretical Dependency between Earnings Volatility and Cost of Capital

According to classical theoretical models, in perfect capital markets, there should be no dependency between earnings volatility and cost of capital because smoother earnings do not affect systematic risk, since they should be diversifiable. Therefore, they will not have an impact on the cost of capital. However, in the presence of market imperfections such as taxes or information asymmetry, income smoothing has the potential to impact the cost of capital (Huang et al. 2009). Poor quality reporting induces information risk, as it affects the coordination and communication between firms and investors (Liu et al. 2002; Francis et al. 2003; Beyer et al. 2010). The commonly held view of the theoretical dependency between accounting information and the cost of capital relies on information asymmetries between firms and investors. Adverse selection creates potential costs between the two factions, when uninformed investors demand additional returns to compensate for their information disadvantage. Accounting information can mitigate such information asymmetries, leading to lower cost of capital (Diamond and Verrecchia 1991; Lambert et al. 2012; Cheynel 2013). The theoretical foundation of this hypothesis critically depends on whether information risk is diversifiable.

Easley and O'Hara (2004) investigate and show how a firm's information structure affects its equilibrium return. They argue that information influences asset prices; therefore, the quantity and precision of accounting information are relevant for asset pricing behavior. Lambert et al. (2007) also examine the impact of accounting information on a firm's cost of capital in the presence of multiple securities and the forces of diversification. Their model is consistent with the CAPM and allows for multiple securities whose cash flows are correlated. They show that the quality of accounting information can influence the cost of capital, both directly and

[3] McInnis (2010) concludes that the coherences of prior empirical evidence, such as Francis et al. (2004), is primarily driven by optimism in analysts long-term earnings forecasts.

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indirectly. If income smoothing reduces information risk, it consequently reduces the cost of capital.

Another possible explanation not directly related to information risk is noise trader risk. De Long et al. (1990) develop the idea that arbitrageurs are forced to liquidate their positions early, because of the risk irrational traders introduce to the market, and thereby influence prices. These noise traders act on erroneous stochastic beliefs and trade on basis of pseudosignals, which they believe carry information. Thus, information such as earnings volatility may be evaluated as valuable information and may deter prices from fundamental values. Building on these theoretical models and the extant empirical evidence, we conclude that earnings volatility influences the cost of capital. In order to examine the trade-off between costly earnings volatility and the expected return of financial derivatives, a comprehensive theoretical model is necessary.

IV.1.3 Model

IV.1.3.1 Research Methodology

In the preceding sections, the research background was specified, and reasonable explanations and causalities were presented. These findings were examined in a research project initiated by a large German bank which needed to reduce earnings volatility due to regulatory and investor requirements. In the wake of this research project, we quantitatively elaborate these causal relationships by developing a theoretical optimization model. We follow the research methodology introduced by Meredith et al. (1989), according to which actual propositions to real-word phenomena are provided by “following a continuous, repetitive cycle of description, explanation and testing.” This cycle process starts in Section 3 with a detailed description of the basic causalities as well as an explanation of the model’s assumptions and objective functions. The process is rounded off in Section 4 with a testing stage, where the accuracy of the theory emerging from the observation and explanation is utilized to demonstrate a hypothetical (but realistic) application of the model. The output of the testing stage often serves as the basis for further description and explanation, thus reactivating the cycle process.

IV.1.3.2 Basic Model Setting

As was discussed in the preceding sections, there are strong indications that volatility in a firm’s income statement induces costs. When transaction costs are ignored, a decline in earnings volatility should become apparent in the total profit, which (among other factors)

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incites managers to report smooth earnings. It is justifiable to assume that an optimal degree of admissible earnings volatility exists, such that the monetary benefit of the reduction in volatility outweighs the decline in expected future returns. Hence, organizations should attempt to ascertain this optimal degree. Subsequently, we elaborate the situation at the outset and introduce the model's assumptions. Consider a time frame $[0, T-1]$ with $t_i \in [0 = t_0, t_1, \dots, t_n = T-1]$, where t_0 denotes the first and $t_n = T-1$ denotes the last point in time to seize the opportunity to take actions related to earnings volatility. In practice, it is possible to react to the earnings volatility at every continuous point in time within a period $[t_i, t_{i+1}]$. To simplify the notation, we use discrete points of time t_i to refer to the entire period, and we do not distinguish at which point in time within this period the reaction takes place.

Assumption 1: *An organization holds at least one fair valued financial derivative with nominal amount x. This transaction was executed at least two periods in advance in* $t_l \in [-\infty, t_{i-2}]$, *so that earnings volatility can be quantified. Further, the portfolio of fair valued financial derivatives is chosen according to the company's optimal conditions with respect to its risk-return profile.*

The following model originates from a financial transaction that has been hedged according to the organization's attitude toward risk and return. It is already optimally hedged with regards to cash flow volatility. However, the identification of transactions that are optimal according to the company's risk-return profile - e.g., in terms of the traditional Sharpe Ratio (Sharpe 1964) or according to more recent time-varying approaches (e.g., Campbell et al. 2005) - does not fully account for the effects triggered by earnings volatility in the income statement. Certainly when hedging cash flow volatility according to the risk-return profile, also earnings volatility is reduced (unless earnings management, via accruals, adds additional variance). But the remaining earnings volatility may still require additional hedging to maximize utility. The earnings volatility is measured in absolute values and in monetary terms, calculated as the standard deviation of the market value changes of the underlying instrument. To calculate the earnings volatility, it is mandatory that the existing transaction has been executed at least two periods in advance, i.e., at any point of time $t_l \in [-\infty, t_{i-2}]$. The possibility of reducing the volatility is achieved through additional time-dependent hedging activities. In the following discussion, these hedging activities are represented by a hedging degree γ_{t_i} that possibly ranges from $\gamma_{t_i} = 0$ up to a full hedge $\gamma_{t_i} = 1$ for any t_i.

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The trade-off presented earlier leads to the objective function $G(\gamma)$ (see Eq. (1)). In order to determine the optimal additional hedging strategy, the difference between the expected return $r(\gamma)$ and the utility associated with costs $c(\gamma)$ has to be maximized.

$$max\ G(\gamma) = max \sum_{t_i=0}^{t_n} G(\gamma_{t_i}) = max\ r(\gamma) - c(\gamma) = \sum_{t_i=0}^{t_n} r(\gamma_{t_i}) - c(\gamma_{t_i}) \qquad (1)$$

However, the optimal hedging strategy depends on not only the expected return of the financial derivative but also the company-specific attitude toward earnings volatility. This is taken into account in the utility function $c(\gamma)$ that represents the utility associated with the costs resulting from earnings volatility (reduction).

IV.1.3.3 Hedging Activities and Costs of Volatility

Assumption 2: *Every hedging activity $\gamma_{t_i} \in [0,1]$ in t_i is executed as a one-to-one hedge exclusively for the purpose of lowering the induced, absolute earnings volatility in period t_{i+1}. There are no transaction costs or liquidity constraints.*

Assumption 2 guarantees that the company's optimal risk-return ratio is retained while accounting for earnings volatility, as a one-to-one hedge adjusts the net amount of the investment. Since the relative earnings volatility of the underlying instrument remains unaffected, there is a proportional relationship between the absolute amount of earnings volatility and the net amount of investment, adjusted by the extent of hedging (γ_{t_i}). The lowest volatility is expected to occur for a hedging degree $\gamma_{t_i} = 1$, which resembles a full hedge, and therefore induces no earnings volatility at all. In contrast, a hedging degree $\gamma_{t_i} = 0$ corresponds to the maximal level of earnings volatility.

Assumption 3: *The utility function $c(\gamma)$ that measures the utility associated with the costs of earnings volatility in imperfect markets increases monotonically and progressively with the amount of earnings volatility.*

To depict the utility associated with the costs of earnings volatility, we assume a monotonic, progressive utility function $c(\gamma)$ that depends on the vector $\gamma = (\gamma_{t_0}, \dots, \gamma_{t_n})$ of the time-dependent hedging activities. The non-linear course of the utility function is strongly supported by prior literature on accounting (see Section 2). It is well known that the probability of default grows disproportionately with the level of uncertainty (Duh 2012).

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Assumption 4: *The organization is risk-averse, and, in an imperfect market, its utility associated with the costs of earnings volatility depends on the (remaining) earnings volatility as well as on the reduction of earnings volatility. Thereby, the remaining earnings volatility contributes positively to the utility function (i.e. induces costs for the company), whereas hedging activities to reduce the earnings volatility contribute negatively to the utility function (i.e. reduces costs for the company compared to unhedged derivatives).*

Based on the evidence of prior empirical literature, the utility function introduced in this study consists of two components. The first part of the utility function quantifies the (remaining) volatility, and the second part rewards the organization's hedging activities that decrease the absolute earnings volatility. Assuming a linear relationship between the hedging level and the absolute amount of earnings volatility (derived from Assumption 2), the residual earnings volatility for each period is given by the factor $\left(1-\gamma_{t_i}\right) \cdot \vartheta_{t_i}^0$, where $\vartheta_{t_i}^0$ is the initial volatility induced by the existing transaction. Consequently, the absolute decline in earnings volatility in every period t_i is given by $\gamma_{t_i} \cdot \vartheta_{t_i}^0$.

We assume that ‘gains’ (in terms of lower costs through a decrease in earnings volatility) and ‘losses’ (in terms of costs through the remaining earnings volatility) are considered differently, in reminiscence of the Prospect Theory approach proposed by Kahneman and Tversky (1979). The utility associated with costs incurred by the remaining earnings volatility should be weighted higher than a possible reduction, which reduces the total costs. Therefore, it is reasonable to assume that an organization's sensitivity toward the remaining earnings volatility (i.e., ‘losses’) exceeds its sensitivity to the reduction of earnings volatility (i.e., ‘gains’). To implement this disparity, we introduce $a, b \in \mathbb{R}$ as the exponents of the respective parts of the utility function that price the remaining earnings volatility and its reduction, respectively. Assuming that $a > b, for\ a, b \in \mathbb{R}$ translates the disparity between the two effects of hedging against earnings volatility. Moreover, this is in accordance with the progressive course of the utility function that was claimed in Assumption 3 as well as Prospect Theory.

Further, let $c_1 \geq 0$ be the cost factor for valuating one unit of the potentiated remaining earnings volatility, and $c_2 \geq 0$ be the factor that reflects the monetary amount with which one unit of the potentiated level of reduction is rewarded. Because of the differences in their business models, different organizations might be willing to incur different levels of earnings volatility in their income statements during a certain period under consideration. The exact

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sizes of the parameters a, b, c_1, and c_2 are deliberately left open and should be set individually by each organization according to its distinct aversion toward earnings volatility. To assess the magnitude of these parameters, the findings of the extant empirical literature on the implications of earnings volatility could be useful (e.g., Francis et al. 2004; Rountree et al. 2008; Duh et al. 2012). Considering all these hypotheses together, the utility function $c(\gamma)$ given in Equation (2) presents our way of quantifying the cost induced by earnings volatility:

$$c(\gamma) = \sum_{\mathrm{t}_i=0}^{\mathrm{t}_n} c(\gamma_{\mathrm{t}_i}) = \sum_{\mathrm{t}_i=0}^{\mathrm{t}_n} \left((1-\gamma_{\mathrm{t}_i}) \cdot \vartheta_{\mathrm{t}_i}^0\right)^a \cdot c_1 - \left(\gamma_{\mathrm{t}_i} \cdot \vartheta_{\mathrm{t}_i}^0\right)^b \cdot c_2. \tag{2}$$

Assumption 5: *The expected profit of the existing transaction at any point of time t_i is described by the return function $r(\gamma_{t_i})$, which depends on the hedging degree γ_{t_i} and the expected yield r_{t_i} in t_i.*

In our model, assuming a one-to-one hedge, every reduction of earnings volatility corresponds to a distinct hedging strategy. In turn, this results in a unique decline in the expected returns of the existing transaction. However, the expected yield r_{t_i} in t_i - e.g., the process given by a Cox, Ingersoll, and Ross model (1985) (CIR model) - does not depend on the amount of investment *x* and the hedging degree γ_{t_i}. The expected absolute return $r(\gamma_{t_i})$ for each hedging degree γ_{t_i} at any point of time within period t_i can be expressed by the linear function $r(\gamma_{t_i}) = x \cdot (1-\gamma_{t_i}) \cdot r_{t_i}$. Consequently, for the entire period under consideration $[0, T-1]$, the expected absolute return $r(\gamma)$ could be obtained by summing up the results for each $r(\gamma_{t_i})$.

$$r(\gamma) = \sum_{t_i=0}^{t_n} r(\gamma_{t_i}) = \sum_{t_i=0}^{t_n} x \cdot (1-\gamma_{t_i}) \cdot r_{t_i}. \tag{3}$$

IV.1.3.4 Objective Function

The expected overall profit - including the effects induced by earnings volatility in the income statement - can be measured by the objective function $G(\gamma)$ introduced in Section (3.2). This objective function describes the monetary amount that any hedging strategy $\gamma = (\gamma_{t_0}, \dots, \gamma_{t_n})$ *c*an achieve by adding the expected return $r(\gamma)$ with the costs of the incurred earnings volatility $c(\gamma)$. Because of the progressive nature of the utility function, the course of the

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objective function is concave (see Figure 1). Consequently, the globally optimal hedging degree ${\gamma_{t_i}}^*$ in t_i is the level where $G(\gamma_{t_i})$ reaches the highest value. The vector of the optimal hedging levels $\gamma^* = ({\gamma_{t_0}}^*, \dots, {\gamma_{t_n}}^*)$ for the entire period under consideration could be obtained by solving the following optimization problem:

$$max\, G(\gamma) = \max \sum_{t_i=0}^{t_n} G(\gamma_{t_i}) \tag{4}$$

$$= \max r(\gamma) - c(\gamma) = \max \sum_{t_i=0}^{t_n} r(\gamma_{t_i}) - c(\gamma_{t_i})$$

$$= \max \sum_{t_i=0}^{t_n} x \cdot (1-\gamma_{t_i}) \cdot r_{t_i} - \left((1-\gamma_{t_i}) \cdot \vartheta_{t_i}^0\right)^a \cdot c_1 + \left(\gamma_{t_i} \cdot \vartheta_{t_i}^0\right)^b \cdot c_2$$

The objective function is maximized for:

$${\gamma_{t_i}}^* = \left\{\gamma_{t_i} \in [0,1] \middle| \frac{\partial G(\gamma_{t_i})}{\partial \gamma_{t_i}} = 0 \wedge \frac{\partial^2 G(\gamma_{t_i})}{\partial^2 \gamma_{t_i}} < 0\right\} \tag{5}$$

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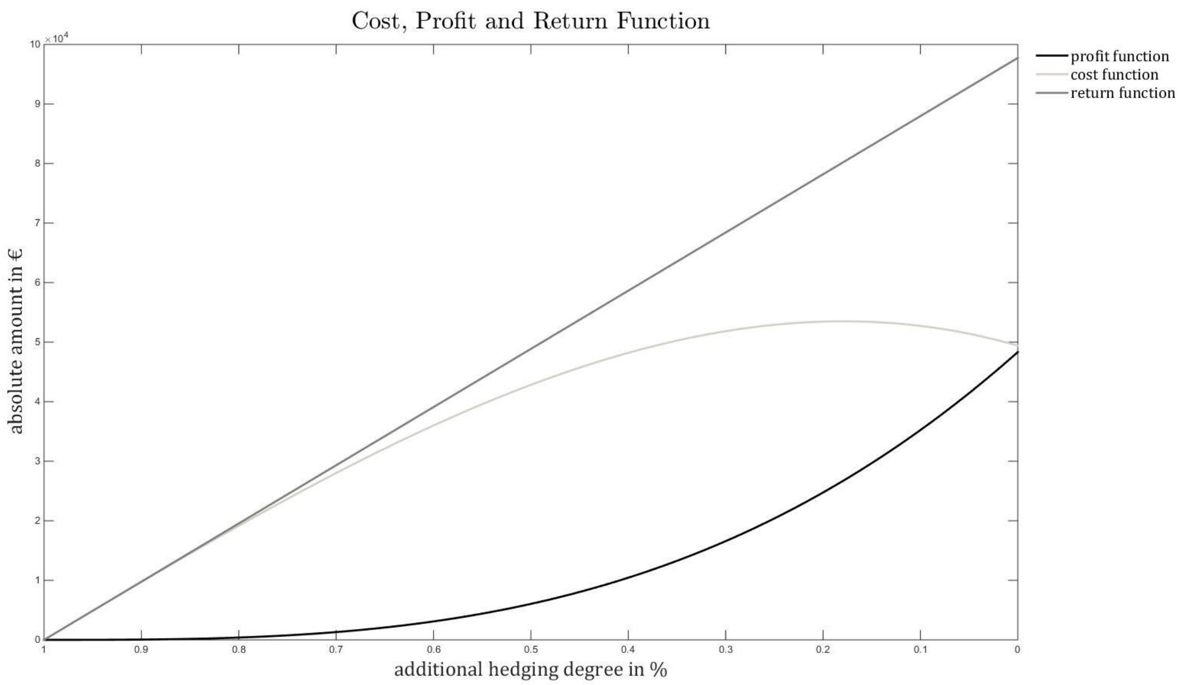

Figure 2 presents an exemplary objective/profit function $G(\gamma_{t_i})$, utility/cost function $c(\gamma_{t_i})$, and return function $r(\gamma_{t_i})$. The objective function in this specific scenario reaches maximum value at $\gamma_{t_i}{}^* = 17.89$ %.

With the help of our model, we established a way to quantitatively elaborate the effect of earnings volatility; thus, we provided a basis for decision-making when trading and reporting fair valued financial derivatives. In order to examine the applicability, advantages, and results of the model further, we conduct an exemplary application and analysis of the model using simulated data in the following section.

IV.1.4 Application

IV.1.4.1 General Setting

In the financial industry, the volatility of accounted earnings is the focus of attention because of the large volume of fair valued financial derivatives in the income statements of firms (Barth et al. 1995; Hodder et al. 2006). We demonstrate the practical applicability of our optimization model by considering the situation of a financial service provider that is willing to sacrifice some potential returns in order to reduce the volatility in the income statement. We consider a bank that holds a 3-month interest rate swap with a nominal of *€10,000,000*

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and a remaining term of five quarters. The transaction is closed as a payer swap with floating payments referenced to the 3-month EURIBOR and a fixed payment rate of *1%*. By applying the proposed model, we can determine a company-specific, optimal hedging strategy for every point of time t_i during the trade's lifetime.

IV.1.4.2 Simulation of Cash Flows

The change in the fair value of an interest rate swap is determined by the change in the fair value of the underlying risk position, which is the 3-month EURIBOR. To obtain the necessary data for optimizing the hedging activities, we apply a Monte Carlo Simulation to generate forecast values of the 3-month EURIBOR for a sufficiently large period. We use the Cox, Ingersoll, and Ross (1985) model (CIR model) for the simulation, since it has been commonly used in the valuation of interest rate derivatives (Bringo and Mercurio 2001). To obtain the exact cash flows of the transaction at the payment dates, we multiply the difference between the simulated data and the fixed rate with the predetermined nominal. The parameterization of the CIR model[4] thereby was adjusted with the bank which initiated the research project. All further parameters in this manuscript had to be changed as the bank did not want their data to go public due to data protection regulations.

IV.1.4.3 Specification of the Cost Function

In the next step, we specify the utility function that was introduced in Section 3.3. We set the parameters to an amount that we expect will reflect a majority of the cases. Even if the parameters chosen are not applicable to all financial institutions, our analyses would serve as a hypothetical demonstration of our optimization model. When applying this model in a financial institution, all the parameters would have to be adapted according to the bank's business model and attitude toward earnings volatility. In this sample application, let $a = 3.0$ and $b = 2.0$ be the power of the sensitivities toward earnings fluctuations and reductions, respectively. Further, we assume the cost factors to be $c_1 = 1.50E$-€3 and $c_2 = 1.00E$-€10.

IV.1.4.4 Determining the Optimal Hedging Strategy

The overall objective function for each t_i with $i = \{0, \ldots, 4\}$ can be determined by subtracting the utility function from the return function. The objective function $G(\gamma)$ can be interpreted as a utility function. The additional hedging degree at which the objective function peaks

[4] The CIR model is calibrated with a mean reversion parameter of a=5.0%, a long-term mean of b=2.0%, volatility of $\sigma = 15\%$ and a starting value of 2%.

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would correspond to the bank-specific optimal additional hedging strategy when earnings volatility is costly.

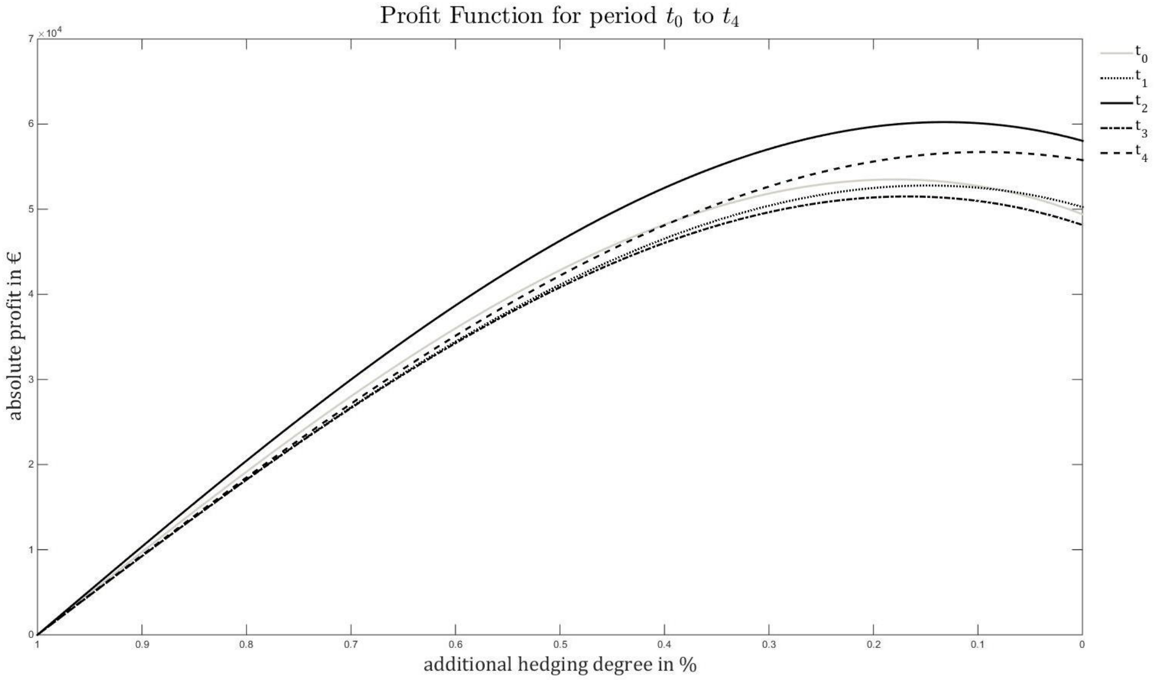

Figure 2 shows the objective/profit function for the periods t_0 to t_4. The function peaks at *0.1798* in t_0, *0.1482* in t_1, *0.1314* in t_2, *0.1676* in t_3, and *0.0956* in t_4.

The optimal hedging degree differs across the periods t_0 to t_4 because of the initial earnings volatility; it ranges from *9.56%* up to *17.98%*. In this case, the point of time t_i, for *i = 0,…,4,* with the highest demand for additional hedging activities corresponds to the moment with the maximum initial volatility. However, this cannot be generalized, as the value of the interest yield also contributes to the determination of the optimal hedging strategy. If, *ceteris paribus*, the interest rate increases, the bank is likely to hedge a smaller amount in order to profit from the higher interest rate. Nevertheless, if there is an increase or decrease in both the expectation on the future interest rate as well as the initial volatility, the optimal additional hedging would depend on the bank's adjustment of the parameters. When there is a maximum adjustment of the optimal hedging level $\gamma_{\boldsymbol{t_i}}{}^*$ of *43.0%* from $\gamma_{\boldsymbol{t_i}}{}^* = 16.76\%$ in t_3 to $\gamma_{\boldsymbol{t_4}}{}^* = 9.56\%$ in t_4, the optimal absolute magnitude of the residual volatility stays within the tight range of less than $\pm$ 5.0% around the mean of *€263,400.* This finding supports the previous observation that a bank internally commits to a certain level of volatility that it is willing to accept.

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IV.1.4.5 Sensitivity Analysis

The introduced model and the parameterization present one possible way to quantify this real-world phenomenon. The parameters of the utility function differ across industries and even across companies. Since a change in the parameters would lead to different results, it is essential to analyze the stability of the model toward a change in the costs parameters. Therefore, we analyze the stability toward c_1 by scaling the initial value of $c_1 = 1.50E$-€3 within the range of $\pm 33.34\%$.

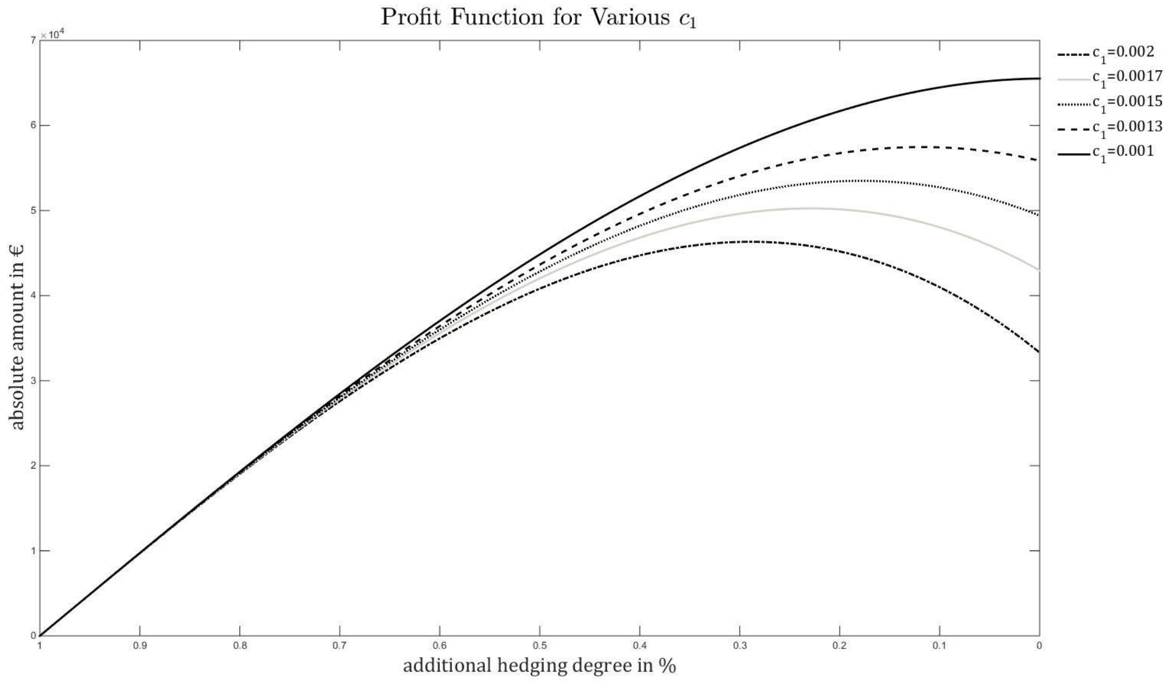

Figure 3 depicts the course of the objective/profit function in response to the variation of the cost parameter c_1.

As expected, for a large c_1 (i.e., high sensitivity toward earnings volatility), the remaining volatility is at an exceptionally high price and strongly detracts the objective function (see Figure 3). Industries or companies with little sensitivity toward fluctuations might price the remaining volatility comparatively low. In such cases, no additional hedging is recommended. Conversely, industries with a strong ambition to report persistent earnings would price the absolute magnitude of residual volatility with an excessive cost factor c_1, which would lead to a comparatively higher optimal hedging degree. Summarizing this analysis, we can

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conclude that a company's attitude toward earnings volatility influences its optimal hedging strategy substantially.

In addition to the sensitivity analysis toward c_1, we examine the effects related to a variation in c_2, which reflects the sensitivity toward the level of reduction of earnings volatility. The magnitude of costs and profit changes with the variation of c_2. The highest absolute profit is observed for the lowest cost factor c_2, and vice versa. Nevertheless, the magnitude of c_2 does not significantly affect the level at which the objective function is maximized. Consequently, the optimal hedging strategy does not change noticeably. Only the absolute monetary amount that is reached at the hedging degree ${\gamma_{t_i}}^*$ differs slightly.

The variations in the exponents a and b have not been considered previously. They represent the organization's weighting of the remaining volatility and reduction, respectively. According to Assumption 3, the weighting factor for the remaining volatility is at least the same size as the weighting factor for the reduction b. Therefore, we expect strong sensitivity toward a change in the parameter a in particular.

IV.1.5 Conclusion and Contributions

Financial institutions have struggled with the high amount of income volatility that has resulted from the fair value accounting of financial derivatives. We attempt a first approach to illustrate how costs through earnings volatility could be taken into account when managing a derivatives portfolio. Thereby, a trade-off arises between the reduction of expected profit and the costs of earnings volatility. Consistent with the extant literature, we develop an optimization model that takes the costs of earnings volatility into account when deciding the optimal hedging strategy.

Our study attempts to contribute to the scientific literature and practice in the following ways. First, to the best of our knowledge, we are the first to propose a utility function for assessing the reduction of earnings volatility (cf. Research Question 1 and 2). The proposed utility function assesses the reduction of earnings volatility considering the total (absolute) volatility reduction resulting from additional hedging activities. Second, when applying the developed utility function in an optimization model, its results can serve as a first indication for decision-making. Thus, it provides initial guidelines for bank managers when deciding on the hedging strategy (cf. Research Question 3). Third, we conduct sensitivity analyses to analyze the relevance of the parameters (cf. Research Question 4). By doing so, we derive first practical

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implications for managing a derivatives portfolio when earnings volatility is costly. To ensure the model's general practicability, we test the model using real-world and simulated data.

IV.1.6 Limitations and Further Research

Our model is associated with several limitations that have to be taken into account when applying the optimization model for decision-making support. (1) Our model neglects non-quantifiable and therefore unhedgeable risk factors, transaction costs, compliance and regulatory requirements, and liquidity constraints. Thus, the model's environment simplifies reality to focus on the described trade-off. (2) Our approach considers only one security at a time. A possible extension of our study is a portfolio approach that considers the diversification effects when there are multiple securities. When managing a portfolio with multiple derivatives, the contrary development of single assets could possibly balance earnings volatility. (3) Our prototypical utility function doubtlessly simplifies matters and needs to be examined more thoroughly in further research. Our proposal for quantifying the costs of earnings volatility is only a first step toward a comprehensive solution. Despite these limitations, our model is the first to quantify the trade-off that arises when considering the costs of earnings volatility in a derivatives portfolio.

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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 main objective of this doctoral thesis is to contribute to the fields of decision support in IT and risk by investigating fundamental aspects of the economic valuation of strategic decisions. After motivating the relevance to provide decision support in general as well as in the special fields of IT and risk, challenges for three particular decision areas - which were addressed in the research papers that are included in this doctoral thesis - were presented:

(i) Providing decision support in IT innovation management

(ii) Providing decision support in credit portfolio management

(iii) Providing decision support in hedging

Regarding the first decision area, the research papers support decision making in IT innovation management by providing concrete guidelines on the usage of software products to improve effectiveness and efficiency of innovation communities and by analyzing the optimal IT innovation investment strategy considering organizational learning (Chapter II).

Regarding the second decision area, the research paper supports decision making in risk by providing concrete guidelines on the application of the statistical method ‘cluster analysis’ in credit portfolio management as well as by analyzing various real-world credit portfolios from a German financial institution (Chapter III).

Regarding the third decision area, the research paper supports decision making in risk by providing a mathematical approach to quantify a company’s earnings volatility induced by fair value accounted financial derivatives as well as by determining the optimal hedging degree regarding earnings volatility (Chapter IV).

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

V.1.1 Results of Chapter II: Decision Support in IT Innovation Management

Chapter II focuses on providing decision support in IT - especially in IT innovation management - by examining two concrete research topics: On the one hand, the opportunities and challenges of three different forms of innovation communities are analyzed. In this context, it is also discussed how digitalization initiatives can improve the effectiveness and efficiency of innovation communities (Section II.1). On the other hand, the economically optimal investment strategy in IT innovations with different maturity and the influence of the crucial determinants are analyzed with the help of a mathematical model (Section II.2 and Section II.3).

- In Section II.1, research paper 1 first demonstrates definitions, opportunities as well as challenges for three different forms of innovation communities (Objective II.1). In this context, the primary goal, the thematic focus, and the participating organizations for the three different innovation community forms knowledge exchange, open innovation community, and internal innovation community are presented. Additionally, the substantial challenges when applying one of the three innovation community types are discussed. As a first result, a possible knowledge drain by the involvement of external units (major challenge for knowledge exchange), the problem of sharing the innovation with others - especially competitors - (major challenge for an open innovation community) and the risk of operational blindness (major challenge in an internal innovation community) are discussed. Furthermore, research paper 1 identifies and evaluates possible digitalization initiatives to improve effectiveness and efficiency of innovation communities (Objective II.2). As a further result, the benefits of SharePoint, HYVE IdeaNet App, Yammer, and RapidMiner through the improvement of collaborative teamwork, interaction, communication and information gathering within innovation communities are presented. Thereby, SharePoint and the HYVE IdeaNet App improve efficiency of the innovation communities (i.e., the factors time-to-market and cost-to-market), whereas RapidMinier particularly improves the effectiveness of innovation communities (i.e., the factors new-to-market and fit-to-market). Furthermore, Yammer contributes to the efficiency as well as to the effectiveness of innovation communities simultaneously. Subsequently, as the last result of this research paper, recommendations for practitioners are presented by proposing a concrete form of an innovation community and suitable portfolios of digitalization initiatives. In this context, a highly innovative market leader should implement an internal innovation community and use RapidMinier in order to maximize the use of internally available knowledge and minimize the risk of knowledge drain to externals. Moreover, an average innovative market participant should consider an open innovation community in accordance with Yammer and the HYVE IdeaNet App in order to improve communication and information exchange and gain knowledge about their potential customers. Furthermore, to establish initial know-how about some subject areas and to enable collaborative teamwork, a below-average innovative market entrant should use the community form knowledge exchange as well as SharePoint. Summarizing, Section II.1 demonstrates specific guidelines for the IT-based support of innovation communities from a practitioner's view.

- In Section II.2, research paper 2 first specifies and evaluates the crucial determinants in strategic IT innovation investment decisions (Objective II.3). Thereby, a list of various company-specific (e.g., investment budget, ability to innovate) and innovation-specific factors (e.g., maturity, probability of success, market impact) as well as their influence on the economic valuation of an IT innovation project are proposed. Furthermore, research paper 2 develops a mathematical model to determine a company's optimal IT innovation investment strategy considering organizational learning (Objective II.4). Especially the implementation of organizational learning - i.e., a company's ability to improve its innovativeness through engaging in IT innovation projects - contributes to scientific literature and enriches existing approaches regarding this topic. As a major result, it is shown that the optimal IT innovation investment strategy should be dynamically adjusted to the company's ability to innovate, which, in turn, varies over time due to organizational learning. Furthermore, it is shown, that even below-average innovative market participants should invest in IT innovations in order to gain knowledge through organizational learning and catch up with the market leaders. Another interesting results relates to the planning horizon. Whereas organizational learning does not play an important role in a short planning horizon of five periods, the influence and therefore necessary adjustments in a longer planning horizon of at least 10 periods is substantial. Last but not least, the paper shows that a company's IT innovation investment strategy converges when the maximal innovativeness is reached, as no further improvement through organizational learning can be realized. Summarizing, Section II.2

demonstrates a mathematical approach to determine and analyze a company's optimal IT innovation investment strategy and therefore supports the human decision maker in strategic IT innovation investment decisions.

- In Section II.3, research paper 3 also develops a mathematical model to determine the optimal allocation of a strategic investment budget to IT innovations with different maturity and simultaneously considers organizational learning. However, in contrast to research paper 2, the primary goal of research paper 3 is to determine and analyze causal relationships in IT innovation investment decisions (Objective II.5) and to determine the evaluation error steaming from fixed compared to dynamic IT innovation investment strategies (Objective II.6). As a first result, it is shown that the company's ability to innovate influences the dynamic adjustment of the IT innovation investment strategy substantially. An average innovative company's optimal investment strategy adjusts most over time, whereas it adjusts less for a below-average innovative and an above-average innovative company. Furthermore, especially the effect of a company's initial ability to innovate and the innovation's expected probability of success on the evaluation error are analyzed in a model considering organizational learning as well as in a model neglecting organizational learning. As another interesting result, it gets clear that the evaluation error in a model considering organizational learning exceeds the evaluation error in a model neglecting organizational learning. Thus, companies neglecting organizational learning may wrongly assume that a fixed strategy is not that disadvantageous. Furthermore, the sensitivity analyses show that a below-average innovative company as well as an innovation's low probability of success decrease the evaluation error and therefore minimize the economic disadvantage of fixed strategies. Summarizing, Section II.3 extends Section II.2 by supporting the human decision maker by means of discussing the substantial relationships in strategic IT innovation investment decisions and demonstrating the relevance of dynamic adjustments in a company's IT innovation investment strategy.

V.1.2 Results of Chapter III: Decision Support in Credit Portfolio Management Considering Risk and Return

Chapter III focuses on providing decision support in risk - especially in credit portfolio management - by examining the suitability of the statistical method ‘cluster analysis’ for decision making in credit portfolio management (Section III.1).

- In Section III.1, research paper 4 first provides a structured approach to analyze credit portfolios from a risk and return perspective using the statistical method ‘cluster analysis’ (Objective III.1). By providing concrete recommendations for the procedure of performing a cluster analysis in the context of credit portfolio management, practitioners are supported and guided regarding a proper implementation. As a major result, the recommendable data transformations, the data standardization and the variable selection are discussed. Thereby, the concrete procedure for three different datasets with up to 25 variables is shown. Moreover, the approach to determine the necessary clustering settings including the choice of the proximity measure, the clustering method, and the number of clusters, as well as an approach to verify and analyze the results is presented. Guiding through this process for credit portfolio management contributes to science and practice. Furthermore, research paper 4 analyzes and evaluates different credit portfolios of a German financial institution by conducting several cluster analyses (Objective III.2). As an interesting result, some clusters in these datasets show unique combinations of the variables customer rate and cost rate. By identifying clusters of credit contracts with specific economical properties, the financial institution, on the one hand, can decide on the quality of credits from an integrated risk/return perspective and deduce recommendations for action - e.g., selling or restructuring clusters of credits. On the other hand, the financial institution can deduce recommendations for the closing of future credits by an ex ante comparison of a new credit contract to the existing clustering. Summarizing, Section III.1 provides specific guidelines for performing a cluster analysis of a credit portfolio from a practitioner’s view and derives concrete recommended actions for the restructuring of three real-world credit portfolios.

V.1.3 Results of Chapter IV: Decision Support in Corporate Hedging Considering Earnings Volatility

Chapter IV focuses on providing decision support in risk - especially for determining the optimal hedging strategy - by examining the influence of fair value accounted financial derivatives on a company's earnings volatility, which, in turn, is considered as a risk factor from an investor's perspective and therefore induces costs of capital (Section IV.1).

- In Section IV.1, research paper 5 first develops a novel approach to quantify the cost of capital induced by earnings volatility (Objective IV.1). At first, the paper provides an extensive scientific literature review about the drivers of earnings volatility as well as the empirical and theoretical dependency between earnings volatility and cost of capital. Based on these findings, the paper develops a mathematical approach to quantify these costs by considering the absolute amount of earnings volatility, the reduction of earnings volatility through hedging, the cost factors valuating the absolute earnings volatility and the reduction of earnings volatility as well as the factors measuring the sensitivity toward the (reduction of) earnings volatility. Furthermore, research paper 5 proposes a mathematical model, which allows to determine a company's optimal hedging strategy considering the costs of earnings volatility induced by fair value accounted financial derivatives (Objective IV.2). The results of the analyses thereby show a substantial hedging degree in order to reduce earnings volatility and thus, an economic advantage. Furthermore, the optimal hedging degree shows a high sensitivity toward the cost factor measuring the earnings volatility, but a low sensitivity towards the cost factor measuring the level of the reduction of earnings volatility. Summarizing, Section IV.1 provides specific guidelines and a quantitative approach for considering earnings volatility in corporate hedging activities.

V.1.4 Conclusion

Summarizing the results of the research papers presented in Chapter II, III, and IV, this doctoral thesis contributes to the existing literature in decision support in IT and risk by investigating fundamental aspects of the economic valuation of strategic decisions. Most notably, this doctoral thesis contributes to the research areas of IT innovation management, credit portfolio management, and hedging by analyzing, adjusting, and further developing existing approaches as described above.

V.2 Future Research

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

V.2.1 Future Research in Chapter II: Decision Support in IT Innovation Management

The limitations of research paper 1 that provide opportunities for future research regarding the digitalization and design of innovation communities are:

- The paper presents four exemplary digitalization initiatives that can help to improve the effectiveness and efficiency of innovation communities. This is obviously just a small part of possible software solutions that could be beneficial. In order to determine a suitable set of digitalization initiatives for a company applying an innovation community, a much more detailed and comprehensive list of digitalization initiatives including their benefits for the success factors new-to-market, fit-to-market, time-to-market and cost-to-market needs to be collected and analyzed. By doing so, companies can achieve a more comprehensive view about the IT-based support of innovation communities. (cf. e.g., Blood 2004; Von Krogh et al., 2003)
- Moreover, the benefits of the digitalization initiatives are currently solely described qualitatively and not quantitatively. In order to decide about the actual application of these initiatives, a well-founded analysis from an economic perspective is necessary. Thereby, not only the expected benefits need to be quantified, but also the expected costs of the introduction and the application as well as the risks associated with the digitalization initiatives. When done properly, companies can use this economic valuation as guideline when deciding on the application of digitalization initiatives in innovation communities. (cf. e.g., Liebowitz, 2003; Smith, 2005)
- Furthermore, the paper does not give additional advices on the optimal design of an innovation community except for the IT-based support with software products. To improve the innovation management processes in an innovation community, various organizational aspects need to be considered. Companies are faced with questions about the concrete composition of the innovation community (e.g.: Which companies or research institutes should be included? Which employees should be included?), the academic and cultural background of the community members (e.g.: Which academic education is needed? Which personality characteristics are needed?), or the

organizational structure within the innovation community (e.g.: What is the optimal project hierarchy? How much individual working time is allocated to the project?). In order to decide about the design of innovation communities from a holistic perspective, companies need guidelines for all these questions. (cf. e.g., Antikainen et al., 2010)

Regarding the optimal budget allocation to IT innovations of different maturity considering organizational learning (cf. research paper 2 and 3), the aspects for future research are:

- The papers solely focus on one specific part of the decision making process - namely the allocation of a strategic investment budget to IT innovations with different maturity. However, the whole decision making process is much more complex and many more decisions need to be made. Companies first need to determine how much, if any at all, of their budget they want to invest in IT innovations or in rather conservative, established, and less risky IT projects. Furthermore, the IT innovations should be analyzed individually in order to gain more in-depth knowledge about the associated investment. The papers do not focus on this aspect, but solely on the maturity of different IT innovations. (cf. e.g., Nagji et al., 2012)
- Although the innovator profile - i.e., how experienced a company is in handling IT innovation (projects) - is included in the paper, the model does not differentiate between companies with regard to their size or their sector. However, a multi-billion dollar company like Google with roughly 60.000 employees (in 2015) certainly needs to be treated differently compared to a small travel operator start-up with very limited financial resources and only a few employees. (cf. e.g., Czarnitzki et al., 2011)
- Moreover, the model in the paper assumes a risk-neutral decision maker that makes the decision based on the expected profit of the investments. However, the risk profiles of IT innovations vary substantially with their maturity level. Consequently, when deciding on the financial engagement in IT innovations and assuming a risk-averse decision maker, the model needs to be adjusted to cover a risk-return integrated view.
- Furthermore, the paper assumes an exogenous market with a constant market's average investment allocation to IT innovations with different maturity. However, when modeling reality as closely as possible, the market certainly should be assumed to be endogenous. On the one hand, effects of the focused company's engagement on the market's average engagement should be considered, as big players like Google or Apple certainly influence the market's average engagement solely because of their size. On the other hand, dynamic market adjustments should be considered, as herd

behavior or a rush in a new technology obviously can change the market's average engagement substantially.

- Finally yet importantly, the model should be examined empirically with real-world data. So far, the theoretical model and its analyses propose first hypotheses, which, however, need to be validated empirically. In this context, especially the parametrization of the model needs to be handled with great care in order to guarantee robust results.

Taken together, these potential research opportunities provide various starting points for further contributions toward enhanced decision support in IT innovation management.

V.2.2 Future Research in Chapter III: Decision Support in Credit Portfolio Management Considering Risk and Return

The major limitations that provide room for future research regarding cluster analysis in credit portfolio management as shown in research paper 4 are:

- Within cluster analyses, many manual steps and decisions are necessary to perform an extensive analysis of the data and to verify the results. The data selection and data transformation, the weighting of the variables, the decision about the distance measure and the concrete algorithm as well as the verification of the clustering so far need to be done manually. The paper gives concrete guidelines about these issues, but cannot provide a fully automated algorithm that could be used without further adjustments. Full automatization most likely will not be possible, but the automatization of some of the steps mentioned above certainly would improve applicability and suitability for practice. (cf. e.g., Remm et al., 2001)
- Moreover, cluster analysis algorithms normally cannot handle highly correlated variables properly. However, when the input variables are analyzed appropriately and highly correlated variables are excluded or underweighted before performing the cluster analysis, the results do not get distorted. Otherwise, the high correlation reduces the influence of other variables by overweighting (almost) redundant information. Providing an appropriate way to handle correlation within cluster analysis certainly would facilitate applicability and acceptance in science and practice.
- One fundamental problem with cluster analysis is the missing possibility to verify the quality of the results. A cluster analysis always provides results - independently from the data, the weighting, the concrete algorithm, and the distance measure. However, as

cluster analysis is a form of unsupervised learning - i.e., the ‘real’ clustering is unknown - a direct comparison of the results to the ‘right solution’ cannot be performed. Therefore, the results can solely be analyzed with regard to the plausibility of the clustering. Nevertheless, some kind of standardized robustness checks of the clustering would be helpful to get an impression of the quality of the results. (cf. e.g., Hennig, 2008; Strehl et al., 2003)

Taken together, these potential research opportunities provide various starting points for further contributions toward enhanced decision support in credit portfolio management.

V.2.3 Future Research in Chapter IV: Decision Support in Corporate Hedging Considering Earnings Volatility

The analysis of a company’s optimal hedging degree by considering the earnings volatility (cf. research paper 5) comes along with the following limitations that could be addressed in future research:

- One major limitation of the paper is the fact that it simplifies from reality concerning some aspects. Whereas the model considers earnings volatility through fair value accounted financial derivatives, it neglects other risk factors - especially factors that are difficult to quantify like noise trading or herd behavior. Furthermore, the model also does not include transactions costs and disregards compliance or regulatory requirements. In addition, liquidity constraints are ignored in the model. Thus, addressing these aspects in future research would extend the paper’s focus of providing a first model for decision support in hedging considering earnings volatility.
- Moreover, the model so far takes only one financial derivative at a time into account when deciding on the optimal hedging degree. However, as financial institutions manage large portfolios of various products, a portfolio perspective would improve the usefulness and applicability for practice.
- Furthermore, the theoretical model built in this paper needs to be examined empirically in order to ensure applicability in financial institutions. By calculating the model with real-world data, a parameterization based on data from a real financial institution, a discussion of the results with employees, and possibly adjustments of the model most likely would deepen the understanding of the economic determinants of hedging strategies in science and practice.

Taken together, these potential research opportunities provide various starting points for further contributions toward enhanced decision support in hedging.

V.2.4 Conclusion

Summarizing, the research papers presented in this doctoral thesis contribute to the fields of decision support in IT and decision support in risk. They especially investigate fundamental aspects of the economic valuation of strategic decisions and address specific challenges in IT innovation management, credit portfolio management, and hedging. Although this doctoral thesis certainly can only answer some selected questions, it contributes to previous work in these areas. As decision support in IT and risk most likely will continue to play an important role in probably almost all business activities and sectors, this doctoral thesis hopefully can provide valuable theoretical and practical insights for some selected topics in the fields of decision support in IT and decision support in risk.

V.3 References

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