

**Essays on Digitalization, Value of Data, and Efficiency
in the Insurance Industry**

DISSERTATION
of the University of St. Gallen,
School of Management,
Economics, Law, Social Sciences
and International Affairs
to obtain the title of
Doctor of Philosophy in Finance

submitted by

Martin Lehmann

from

Germany

Approved on the application of

Prof. Dr. Martin Eling

and

Prof. Dr. Alexander Braun

Dissertation no. 5000

Difo-Druck GmbH, Untersiemaun 2020

The University of St. Gallen, School of Management, Economics, Law, Social Sciences and International Affairs hereby consents to the printing of the present dissertation, without hereby expressing any opinion on the views herein expressed.

St. Gallen, May 25, 2020

The President:

Prof. Dr. Bernhard Ehrenzeller

Acknowledgement

First, I would like to express my sincere gratitude to my supervisor, Martin Eling, for his continuous support, motivation, and guidance. His persistence and his aim for perfection helped and inspired me in all the time of research and writing. I am very thankful that he has shared his passion for research and academic life with me. Moreover, I would like to thank my co-supervisor, Alexander Braun, for his encouragement and numerous motivational discussions on and beyond research topics. In addition, I would like to thank my co-authors, Christian Biener and Philipp Schaper, for their great advice and collaboration on improving the quality of this dissertation.

Furthermore, I would like to thank my colleagues and friends at the Institute of Insurance Economics (I.VW) for their feedback, support, and discussions. Without them working at the I.VW would not have been as much fun.

Grosser Dank gilt darüber hinaus meinen Eltern, Martina und Frank, die mich bei jeglichen Entscheidungen immer unterstützen und auf die ich immer zählen kann. Ihr seid die Besten!

Lastly, special thanks to my wife, Barbara, on whose support I can always count. Especially in the last months of my dissertation she kept me motivated and she always put a smile on my face. I cannot imagine how the last years would have been without her.

St. Gallen, July 2020

Martin Lehmann

Table of Contents

Acknowledgement	I
List of Figures	V
List of Tables.....	VI
Summary	VII
Zusammenfassung.....	VIII
Essay I: The impact of digitalization on the insurance value chain and the insurability of risks.....	1
1 Motivation and aim of the paper.....	2
2 Research approach	3
2.1 Literature review.....	3
2.2 Conceptual frameworks: value chain and insurability criteria	4
3 Summary of existing knowledge on digitalization in insurance	5
3.1 What is digitalization and which technologies will influence the industry?	5
3.2 What is the impact of these technologies on the value chain?.....	7
3.3 Will the insurance industry lose parts of its value chain to other industries?	12
3.4 Can insurtechs significantly disrupt the industry?	13
3.5 How does the insurability of risks change?.....	15
4 Derivation of potential future work	18
4.1 What should the insurance industry do in response to digitalization?	18
4.2 What future academic research is needed?	20
References	22
Appendix A Dataset of papers and industry studies	29
Appendix B Definitions of digitalization	36
Appendix C Value-chain and technology matrix	37
Essay II: Balancing the desire for privacy against the desire to hedge risk.....	38
1 Introduction	39
2 The value of personal data	41
3 Experimental design.....	43
3.1 Insurance game	44
3.2 Treatments.....	44
3.3 Preference measures and personality characteristics	45
3.4 Procedures and sample characteristics	46
4 Experimental results.....	49
4.1 Main results.....	49

4.2 Heterogeneous treatment effects	52
5 Conclusion.....	55
References	58
Appendix A Tobit regression results	62
Appendix B Experimental materials.....	62
B.1 General information	62
B.2 Overview compensation.....	63
B.3 Introduction first lottery game	63
B.4 Decisions first lottery game	64
B.5 Exemplary introduction of the T _{20-1h} insurance game condition.....	66
B.6 Decisions insurance game	67
B.7 Privacy questionnaire	67
B.8 Numeracy tasks	68
Essay III: Utilization of input factors in the German property and casualty insurance industry.....	69
1 Introduction	70
2 Literature review	71
3 Evidence on labor utilization and hypotheses development	74
4 Sample data and methodology	78
4.1 Data sources	78
4.2 DEA methodology	79
4.2.1 Output	80
4.2.2 Input and input prices	80
4.3 Utilization analysis	82
5 Empirical results	84
5.1 Efficiency levels and utilization of inputs.....	84
5.2 Labor utilization.....	87
5.3 Equity utilization.....	89
6 Conclusion.....	91
Appendix A: Equity and debt capital costs regression results	97
Appendix B: Correlation matrix	97
Appendix C: Robustness tests.....	98
Appendix D: Efficiency comparison direct vs. non-direct insurers.....	101
Essay IV: The relationship between management change and firm performance: evidence from the German property and casualty insurance industry	103
1 Introduction	104

2 Literature review	106
2.1 The impact of firm performance on management turnover	106
2.2 Firm performance after management turnover	108
2.3 Evidence from the insurance industry	110
3 Hypotheses	113
4 Sample data and methodology	114
4.1 Data sources	114
4.2 Firm performance	115
4.2.1 Input and input prices	116
4.2.2 Output and output prices	117
4.3 Regression analysis	118
4.3.1 Impact of firm performance on management board changes	118
4.3.2 Influence of changes in the management board on firm performance	120
5 Empirical results	121
5.1 Impact of firm performance on executive board changes	121
5.1.1 Impact of firm performance on CEO change	121
5.1.2 Impact of firm performance on non-CEO change	125
5.2 Firm performance after management turnover	127
5.2.1 Firm performance after CEO turnover	127
5.2.2 Firm performance after non-CEO turnover	129
6 Conclusion	130
References	132
Appendix A: Correlation matrices	136
Appendix B: ROE, ROA and relative ROA as performance measures	138
Curriculum Vitae	140

List of Figures

Figure 1. Research approach with three clusters and seven key questions.	3
Figure 2. Insurance-specific value chain based on Porter (1985) and Rahlfs (2007). ...	4
Figure 3. Mean WTP relative to expected value of insurance policy.	50
Figure 4. Average proportion of safe choices and CRRA coefficients density plots for RUM and RPM.	53
Figure 5. Relative WTP and average treatment effect conditional on risk aversion. ..	54
Figure 6. Development of DEA efficiency scores over time.	86
Figure 7. Development of equity and labor over-/ under-utilization over time.	86
Figure 8. Potential cost savings per input.	86

List of Tables

Table 1. Insurability criteria and related requirement defined by Berliner (1982)	4
Table 2. List of digital technologies.....	6
Table 3. Impact of digitalization on the insurer's value chain	10
Table 4. Impact of digitalization on insurability of risks (Berliner, 1982)	17
Table 5. Summary of results.....	18
Table 6. Experimental treatment conditions	45
Table 7. Summary statistics and balancing checks.....	48
Table 8. Hypotheses and results from Cummins and Nini (2002)	73
Table 9. Summary statistics for inputs, input prices, and outputs.....	82
Table 10. Summary statistics for firm characteristics.....	84
Table 11. Regression results for labor utilization	88
Table 12. Regression results for labor utilization over time.....	89
Table 13. Regression results for equity utilization	90
Table 14. Regression results for equity utilization over time.....	91
Table 15. Summary of existing literature.....	112
Table 16. Summary statistics for inputs, input prices, outputs, and output prices.....	118
Table 17. Summary statistics of dependent and independent variables	121
Table 18. Probit regression results on CEO turnover	123
Table 19. Probit regression results on nonroutine CEO turnover.....	124
Table 20. Probit regression results on routine CEO turnover.....	125
Table 21. Probit regression results on non-CEO turnover.....	126
Table 22. OLS regression results on efficiency change	128
Table 23. OLS regression results on efficiency change for nonroutine turnover	128
Table 24. OLS regression results on efficiency change for routine turnover	129
Table 25. OLS regression results on efficiency change for non-CEO change.....	130

Summary

This dissertation focuses on the issues of digitalization, the effects of data sharing, and performance measurement within the insurance industry. In the first two essays, "The Impact of Digitalization on the Insurance Value Chain and the Insurability of Risks" and "Balancing the Desire for Privacy Against the Desire to Hedge Risk", we concentrate on digitalization and the effect of data sharing. Within the following papers, "Utilization of Input Factors in the German Property and Casualty Insurance Industry" and "The Relationship between Management Change and Firm Performance: Evidence from the German Property and Casualty Insurance Industry", we analyze productivity in the German property and casualty insurance industry and consider the effects on management.

In the first paper, "The Impact of Digitalization on the Insurance Value Chain and the Insurability of Risks", we closely examine the effects of digitalization on the value chain of insurance companies and the insurability of risks. Based on our findings, we identify research questions and key areas of change for insurance managers.

In the following, the second paper, "Balancing the Desire for Privacy Against the Desire to Hedge Risk", explores the effects of data sharing on the willingness of insurance policyholders to pay for a new contract. For this purpose, an experiment with around 500 participants has been conducted.

The third paper, "Utilization of Input Factors in the German Property and Casualty Insurance Industry", tackles the research question of how German property and casualty insurers use the production factors labor and capital over time. Additionally, an analysis on the differences that occur between insurance companies has been carried out. For the purpose of the study, a database of German property and casualty insurers for the period of 1956 to 2015 has been created.

This database also serves as the basis for the fourth paper "The Relationship between Management Change and Firm Performance: Evidence from the German Property and Casualty Insurance Industry". The aim is to analyze the interaction between performance and management change. The analysis is not limited to CEOs but covers the entire management board.

Zusammenfassung

Die vorliegende Dissertation behandelt die Themen Digitalisierung, Auswirkungen des Datenteilens und Performance-Messung in der Versicherungsindustrie. In den beiden Arbeiten, «The Impact of Digitalization on the Insurance Value Chain and the Insurability of Risks» und «Balancing the Desire for Privacy Against the Desire to Hedge Risk», liegt der Fokus auf den Themen Digitalisierung und Auswirkungen des Datenteilens. Die beiden anschliessenden Arbeiten, «Utilization of Input Factors in the German Property and Casualty Insurance Industry» und «The Relationship between Management Change and Firm Performance: Evidence from the German Property and Casualty Insurance Industry», analysieren die Produktivität in der deutschen Schaden- und Unfallversicherung und betrachten die Auswirkungen auf das Management.

In der ersten Arbeit «The Impact of Digitalization on the Insurance Value Chain and the Insurability of Risks» werden die Auswirkungen der Digitalisierung auf die Wertschöpfungskette von Versicherungsunternehmen und die Versicherbarkeit von Risiken untersucht. Darauf aufbauend sind Forschungsfragen und Anknüpfungspunkte für Versicherungsmanager erarbeitet worden.

Anknüpfend an die erste Arbeit wird im zweiten Teil «Balancing the Desire for Privacy Against the Desire to Hedge Risk» untersucht, welche Auswirkungen das Teilen von Daten auf die Zahlungsbereitschaft der Versicherungsnehmer bei einem neu abzuschliessenden Versicherungsvertrag hat. Zu diesem Zweck ist ein Experiment mit ca. 500 Teilnehmern durchgeführt worden.

In der dritten Arbeit «Utilization of Input Factors in the German Property and Casualty Insurance Industry» wird die Forschungsfrage diskutiert, wie deutsche Schaden- und Unfallversicherer die Produktionsfaktoren Arbeit und Kapital im Laufe der Zeit verwenden und welche Unterschiede dabei zwischen den Versicherungsunternehmen auftreten. Zum Zweck der Untersuchung ist eine Datenbank der deutschen Schaden- und Unfallversicherer von 1956 bis 2015 erstellt und verwendet worden.

Diese Datenbank bildet auch die Grundlage für die vierte Arbeit «The Relationship between Management Change and Firm Performance: Evidence from the German Property and Casualty Insurance Industry». Ziel dieser Arbeit ist es, die Wechselwirkung zwischen Performance und Vorstandswechsel zu analysieren. Die Analyse beschränkt sich dabei nicht nur auf den Vorstandsvorsitzenden, sondern umfasst das gesamte Vorstandsgremium.

Essay I: The impact of digitalization on the insurance value chain and the insurability of risks

Abstract

Based on a dataset of 84 papers and industry studies, we analyze the impact of digital transformation on the insurance sector using Porter's (1985) value chain and Berliner's (1982) insurability criteria. We also present future research directions from the academic and practitioner points of view. The results illustrate four major tasks the industry is facing: enhancing the customer experience, improving its business processes, offering new products, and preparing for competition with other industries. Moreover, we identify three key areas of change with respect to insurability: the effect of new and more information on information asymmetry and risk pooling, the implications of new technologies on loss frequency and severity, and the increasing dependencies of systems through connectivity.

Keywords

Digitalization, value chain, insurability, innovation, technology

Martin Eling, Martin Lehmann (2018).

This paper was presented at the 2017 annual meeting of the Asia Pacific Risk and Insurance Association (APRIA) in Poznan.

This paper has been published in *The Geneva Papers on Risk and Insurance – Issues and Practice*, 43, 359–396.

1 Motivation and aim of the paper

While digitalization—the integration of the analogue and digital worlds with new technologies—has already substantially transformed many other industries,¹ industry commentators believe that the transformation of the insurance industry has come rather late (Müller et al., 2015) and that it has yet to exploit the full potential of digital technologies (Catlin, Hartmann, Segev, & Tentis, 2015). Still, most market participants believe that digitalization will fundamentally change the value creation of this industry, with manifold new ways of customer interaction, new business processes, new risks and new products.² Moreover, recent advances in insurtech have triggered an immense interest among practitioners worldwide. Given this transformation and the magnitude of interest, it seems astonishing that up to now the academic discussion on digitalization has been virtually non-existent.

This paper is a comprehensive review of the impact of digitalization on the insurance industry. It establishes a database of studies, articles and working papers and systematically evaluates the impact of digitalization in light of Porter's (1985) value chain and Berliner's (1982) insurability criteria. Based on the review results, we derive potential future work from the perspectives of industry and research. We do this to provide insurance practitioners and academics with a high-level overview of the main research topics and to encourage future academic work in this field. The focus of the analysis is on the business and economics literature in the risk and insurance domain. To structure our discussion, we organize the paper into three clusters and seven core topics (see Figure 1). The first step is to analyze the main technologies which influence the insurance sector. Based on the results, we describe the impact of those technologies on the insurers' value chain and derive the consequences for the insurability of risks; here we also discuss whether insurance companies will lose substantial parts of their business to other industries or to insurtech companies.

The remainder of this paper is structured as follows. We begin with a short description of our research methodology (Section 2). Then, we review the literature on our five core

¹ See, for example, Moreau (2013) on the music industry or Chathoth (2007) on the travel industry; we also refer to Back, Berghaus, and Kaltenrieder (2016) and Kane, Palmer, Phillips, Kiron, and Buckley (2015) for cross-industry comparisons on the importance of digitalization.

² Dozens of media articles and studies analyze the impact of new technologies on customer satisfaction and loyalty (e.g., Maas & Bühler, 2015; Moneta, 2014), on the improvement of cost structure and business processes (e.g., Berger, Broer, & Pankoke, 2016; Catlin et al., 2016; Chester, Clarke, & Libarikian, 2016), on the future workforce (e.g., Johansson & Vogelgesang, 2015), and on the insurability of new risks (e.g., Biener, Eling, & Wirfs, 2015, for cyber risk). These industry studies focus on specific digitalization trends and their strategic implications; none of them offer an overview of the existing knowledge on digitalization.

research topics (Section 3). Finally, we discuss potential areas of work from both practitioners' and researchers' perspectives (Section 4).

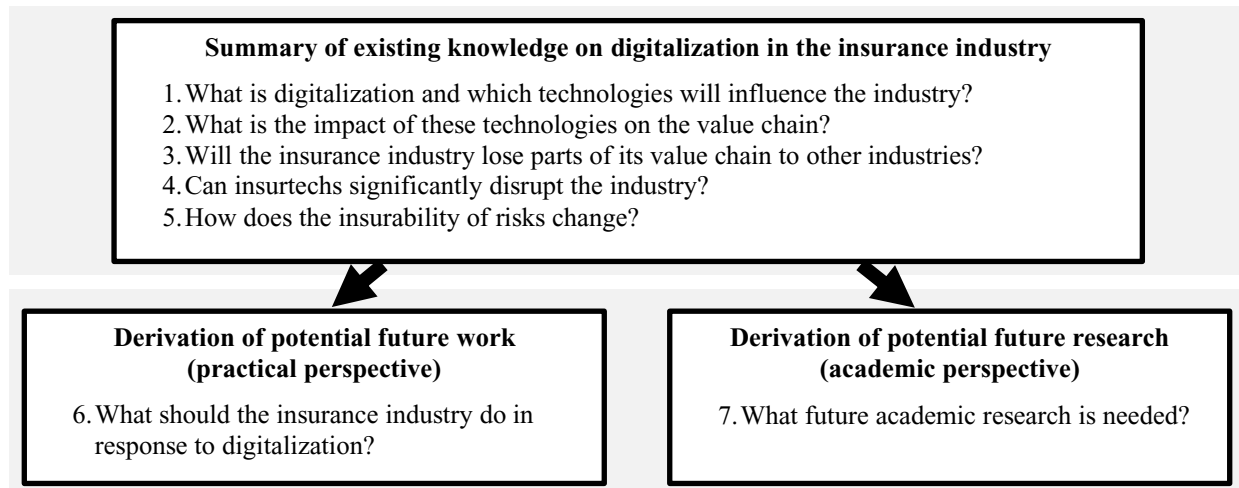


Figure 1. Research approach with three clusters and seven key questions.

2 Research approach

2.1 Literature review

Our literature review consists of a structured and standardized search and identification process that has been used in numerous academic papers (e.g., Biener & Eling, 2012; Biener, Eling, & Wirfs, 2015; Eling & Schnell, 2016). We review the academic literature by searching for the terms “digitalization & insurance,” “technology & insurance,” “artificial intelligence & insurance,” “big data & insurance,” “machine learning & insurance,”³ “internet of things & insurance,” “telematic & insurance,” “cloud computing & insurance,” “blockchain & insurance,” “smart contracts & insurance,” “robo advisor & insurance,” “value chain & insurance,” “insurtech,” and “digitalization & insurability,” in the journal databases EBSCOhost (Business Source Premier and EconLit) and ABI/INFORM Collection.⁴ We then review journal issues from January 2000 to May 2017 of a predefined list of journals related to insurance.⁵ Moreover, we review all working papers from the annual meetings of the American Risk and Insurance Association (ARIA) for 2011, 2012, 2013, 2014 and 2016, the World Risk and Insurance Congress 2010 and 2015 and the European Group of Risk and Insurance Economists conferences 2011, 2012, 2013, and 2016. Finally, we review citations in the identified papers to explore additional relevant material. In addition, we

³ In our paper, we do not focus on literature on algorithms and computational methods. Regarding these topics, we refer for example to Salcedo-Sanz, Cuadra, Portilla-Figueras, Jiménez-Fernández, and Alexandre (2013).

⁴ We also searched “digitization” instead of “digitalization.” The results were often the same, even though the words are typically defined differently. See Section 3.1.

⁵ Journal of Finance, American Economic Review, Journal of Risk and Insurance, Insurance: Mathematics and Economics, Geneva Papers on Risk and Insurance – Issues and Practice, The Geneva Risk and Insurance Review, Journal of Insurance Regulation, and Risk Management & Insurance Review.

search for the keywords in the Social Science Research Network (SSRN) and via Google Scholar. We also identify numerous industry studies with these key words by performing a regular Google search. Based upon this selection process, a database of 84 papers (see Appendix A) is set up and the main results are extracted.

2.2 Conceptual frameworks: value chain and insurability criteria

For the presentation of the results we use two conceptual frameworks. The value chain (Porter, 1985) distinguishes between the primary and supporting activities a firm needs to deliver a product or service. Because Porter's (1985) value chain was formulated for the general industry, we adapt it using the insurance-specific value chain by Rahlfs (2007) (see Figure 2).

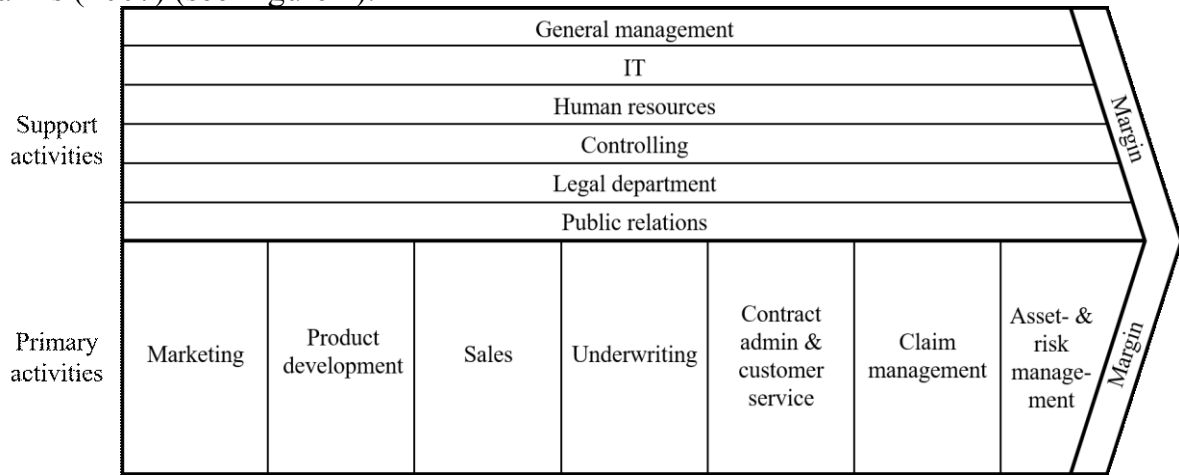


Figure 2. Insurance-specific value chain based on Porter (1985) and Rahlfs (2007).

We also rely on Berliner's (1982) insurability criteria, a frequently used and comprehensive approach for differentiating between insurable and uninsurable risks. Nine insurability criteria cover five actuarial, two market-specific and two societal aspects of insurability (see Table 1). Biener et al. (2015) use this approach to determine the insurability of cyber risks. We refer to Berliner (1982) and Biener et al. (2015) for further details on the criteria.

Table 1. Insurability criteria and related requirement defined by Berliner (1982)

<i>Insurability criteria</i>	<i>Requirements</i>
Actuarial	
(1) Randomness of loss occurrence	Independence and predictability of loss exposure
(2) Maximum possible loss	Manageable
(3) Average loss per event	Moderate
(4) Loss exposure	Loss exposure must be large enough
(5) Information asymmetry	Moral hazard and adverse selection not excessive
Market	
(6) Insurance premium	Cost recovery (insurer) and affordable (policyholder)
(7) Cover limits	Acceptable
Society	
(8) Public policy	Consistent with social values
(9) Legal restrictions	Allow the coverage

3 Summary of existing knowledge on digitalization in insurance

3.1 What is digitalization and which technologies will influence the industry?

In a first step, we scan through all articles and studies for different definitions of “digitalization” and compare them (see Appendix A).⁶ Ingleton, Ozler, and Thomas (2011) describe digitalization in a narrow way and in technical terms such as the availability of digital data: every detail of life is stored in interconnected databases, resulting in a real-time exchange of information. With a broader focus on the business consequences, Tischhauser, Naumann, Candreia, Treier, and Senser (2016) characterize digitalization as the use of new technologies to industrialize and automatize processes, to change the communication between customer and insurer, and to generate and evaluate new data.⁷ Hiendlmeier and Hertting (2015), Müller et al. (2015) and Catlin et al. (2015) describe digitalization as a combination of different components. Whereas Hiendlmeier and Hertting (2015) determine analytics, processes, business impact, technology, mobility and data as the six components of digitalization, Müller et al. (2015) and Catlin et al. (2015) also consider a digital customer experience and customer centricity in their definition. Back et al. (2016) offer the broadest definition, comprising strategic and cultural elements: the digital transformation is characterized by the changes in corporate strategy, business model, processes and corporate culture caused by technologies with the aim of enhancing competitiveness.

We choose a middle way between the broad and narrow definitions and define digitalization for the purpose of this paper as “the integration of the analogue and digital worlds with new technologies that enhance customer interaction, data availability, and business processes.” This definition and the discussions in this paper focus on the economic consequences of digitalization, but digitalization goes beyond economics; for instance, the societal consequences such as the change in human behavior or the ethical frontiers of digital monitoring must be considered. We briefly discuss these topics, but they are beyond the scope of this paper.

In Table 2, we list all technologies which are discussed in the reviewed studies,⁸ define them, and explain the extent of their implementation in the insurance industry. In the

⁶ The terms “digitization” and “digitalization” are sometimes used synonymously and sometimes not. “Digitization” is often defined in the technical context of making analogue data digitally available (e.g. Ingleton et al., 2011; Breeding, 2012), for example, scanning of paper contracts. In contrast, “digitalization” is a broader description of the transformation of the economy and the society.

⁷ Also, focusing on the business, but in a more abstract way, Dörner and Edelman (2015) describe “digitalization” as a process of “creating value in a new business environment,” “creating value in the customer experience” and “building capabilities to support this structure.”

⁸ We do not discuss virtual reality which has been mentioned by some studies but whose applications to insurance have not yet been developed.

table we can identify three broad categories of change in the insurance industry: 1) new technologies change the way insurers and customers interact (e.g., social media, chatbots and robo-advisor); 2) new technologies can be used to automatize, standardize, and improve the effectiveness and efficiency of business processes (e.g., online sales, digital claims settlement); and 3) new technologies create opportunities to modify existing products (e.g., telematics insurance) and to develop new ones (e.g., cyber insurance).

Table 2. List of digital technologies

<i>Technologies</i>	<i>Explanation</i>	<i>Status quo in the insurance industry</i>
Panel A: Technology for data acquisition and analysis		
Artificial intelligence	- Science and engineering of making intelligent machines (McCarthy, 2007). - AI covers the process of analyzing (big) data (e.g., with machine learning methods) and automated decisions making based on that data (PWC, 2016).	- Japanese insurer Fukoku Mutual Life uses IBM's Watson Explorer for automated payout calculation (still subject to human approval; McCurry, 2017). - By analyzing a picture of the insured, Lapetus can estimate the relevant data for a term life policy. The conclusion of the contract can be processed much faster. - Also, AI is used in chatbot applications.
Big data	- Large (partly unstructured) data, which are, for example, generated by telematics devices, social networks or other internet sources. - Different data types (e.g., text, audio, video) from many data sources.	- Many insurers use text mining, e.g., for fraud detection or analysis of web content for customer acquisition. 26 percent of German insurers are using big data analytics and 46 percent have developed a big data strategy (Bitkom & KPMG, 2016).
Internet of things	- Connected world; every element is sending and receiving information through sensors. - Sub-topics: telematics devices, smart home, smart factory.	Telematics devices are starting to be more integrated in health insurance (e.g., vitality program from Generali) and motor insurance (e.g., Progressive, State Farm).
Panel B: Technology for data storage		
Blockchain	- Decentralized database of all digital transactions among participants (Crosby, Nachiappan, Pattanayak, Verma, and Kalyanaraman, 2016). - Contracts could be stored and automatically executed (smart contracts).	- Aegon, Allianz, Munich Re, Swiss Re and Zurich have founded the blockchain Insurance Industry Initiative B3i to analyze the potential (Swiss Re, 2016a). - Allianz and Nephila piloted the blockchain technology for cat swap transactions (Allianz, 2016). - Fizzy by AXA has developed a peer-to-peer flight insurance based on the blockchain technology which pays automatically without any claim filing if a flight is delayed by more than two hours.
Cloud computing	Files stored online and therefore accessible anywhere at any time.	87.5 percent of all financial institutions use cloud services, but with a limited range (Naydenov, Liveri, Dupre, & Chalvatzi 2015).
Panel C: Technology for communication and sales		
Mobile devices with apps	- Smartphones/ tablets with their applications replace desktop computers. - People are always online because of mobile internet access.	- Apps are used for claims reporting (e.g., Allianz, Debeka) and sometimes for contract administration and customer service (e.g., Allstate). - Insurtech Trov and Lemonade use solely an app for their insurance products. - Apps can be used for a more efficient sales process. Agents and brokers can be supported by a variety of tools (e.g., electronic signature, task and time management).

Table 2. List of digital technologies (continued)

<i>Technologies</i>	<i>Explanation</i>	<i>Status-quo in the insurance industry</i>
Panel C: Technology for communication and sales (continued)		
Chatbots	• Software that uses artificial intelligence to advise or support customers. • Communication usually via webpage or apps with built-in chat programs.	• Chatbots are already used for service queries (Huckstep, 2017). • Chatbot SPIXII takes user data for a tailored conversation to automatically sell insurance products (Huckstep, 2017).
Robo-advisors	• Automated asset management. • Customers determine the riskiness of his assets and an algorithm trades automatically.	• Many robo advisors do already exist in the retail business (e.g., Scalable Capital). • Moneypark uses a robo-advisor to consult in asset management (Cash, 2016).
Social network (Facebook)/ Messenger (WhatsApp)/ internet forum	• Platforms for private persons and organizations to share information (statements, pictures, videos). • Messenger services have replaced text messages, starting to get more attention than social networks. • Internet forums provide an easy way to get help for frequently asked topics.	• Facebook is often used by insurance companies. • Some have also started to use messenger services, e.g., Ergo uses WhatsApp for customer service. • Forums are used to screen feedback of customers, to intervene in case of queries, and to communicate actively with (potential) customers.
Video calls (Skype, Facetime)	• Visual phone call, where you can see and interact with others and present sales material.	• Video calls are used in the sales process (e.g., Ergo Direkt). • Also, insurers offer telemedicine via video (e.g., telehealth program by Anthem Blue Cross).
Video platforms (YouTube, Vimeo)	• Videos with a wide variety of topics (instruction manuals, entertainment, product testing, sports, etc.) shared on a platform in the internet.	• Most large insurance companies (e.g., Allianz, Axa, Allstate, Swiss Life) have their own YouTube channel, e.g., for advertisement and product explanations.
Website	• Insurers present various information on the company, the products etc. • Insurers offer policies via websites.	• Used by all insurance companies in the life and non-life segment. • Also, new players that focus on online sales only (e.g., CosmosDirect, smile.direct). • First contact either via own websites or aggregators (e.g., Check 24, Comparis).

3.2 What is the impact of these technologies on the value chain?

Table 3 analyzes the potential impact of the new technologies (see Table 2) on the value chain of insurance companies.⁹ Referring to the three principal categories of change discussed in Section 3.1., the first obvious impact on the value chain is the way insurance companies interact with their customers (e.g., sales, customer service) and how they adapt to their behavior.¹⁰ Whereas customers traditionally needed personal interaction

⁹ A high-level summary of the technology impact on the value chain is also presented in Appendix C (the so-called “value-chain and technology matrix”).

¹⁰ Bieck and Tjioe (2015) find that people under the age of 30 are more open to non-traditional insurance providers (e.g. auto dealers, retailers). Bieck, Marshall, and Patel (2014) find that future customers will be less price sensitive, will seek advice, want personal multi-channel interaction, and be open to new products. Concentrating on the motor insurance segment, Barwitz, Block, Maas, and Nützenadel (2016) define four customer segments based on the interaction between customers and insurers, independent of socio-demographics: utilitarians change the interaction frequently, depending on their personal benefit; hedonists prefer a high-quality and personal interaction; cost-minimizers want to reduce money and time investments;

(agent, broker, bank, etc.) for product information, today they get most information online and directly compare products and prices via aggregator platforms. Some products can be purchased online without any personal interaction.¹¹ Also in later stages of the value chain, digital technologies such as apps offer assistance and support claim reporting.

The second obvious change concerns the digitalization of all processes along the value chain, leading to the automatization of business processes (e.g., automated processing of contracts, automated reporting of claims) and decisions (e.g., automated underwriting, claim settlement, product offerings). While transaction-intensive industries like health insurance are already widely using background processing,¹² the use of big data will trigger a further automatization wave in the insurance industry.¹³ At least two challenges arise in using big data. First, insurance companies need a workforce and tools to analyze large, often unstructured datasets which are generated by telematics devices, social networks, or other internet sources (e.g., customer feedback, pictures, videos).¹⁴ Second,

relationalists prefer personal interaction and stay loyal to their agent. Catlin, McGranahan, and Ray (2013) define nine customer segments, depending on the preferences for price, brand, loyalty, convenience and personal advice.

¹¹ One important aspect in this context is that customers research online, but then purchase offline via traditional channels (ROPO). For example, 84 percent of German consumers gather information online to buy insurance products, but the majority purchase them offline (59 percent research online and purchase offline – ROPO); only 25 percent are pure online customers (Zurich, GfK, & Google, 2016). The ROPO behavior also depends on the product type: whereas 77 percent of pension plans are researched online and purchased offline, this only holds for 50 percent of motor insurance plans. One resulting challenge for insurance companies is the need to create a uniform customer journey, i.e., the customer expects to get the same information in the same quality at any time and through any channel (Pain, Tamm, & Turner, 2014). Also noteworthy are the large differences across countries when it comes to aggregators. While for example in Germany 41 percent of insurance customers use aggregators for the evaluation of motor insurance policies, only 27 percent of Swiss and 23 percent of Austrians use them (Barwitz et al., 2016).

¹² Maas and Bühler (2015) find that today on average 41 percent of processes are automated in the German, Swiss and Austrian insurance industry and health insurers have already automatized 47 percent of processes; they estimate automatization will increase by 28 percent, leading to an average cost saving of 14 percent. Catlin et al. (2015) note in their global study that 70 percent of processes today are done mostly manually, 25 percent are partially automated, and only 5 percent are fully automated; through digitization, only 15 percent of processes will still be done mostly manually whereas 50 percent will be semi-automated and 35 percent fully automated; it is possible to save 30 to 50 percent in non-commission costs through automatization. Note that neither of the studies mention a time period for reaching full potential.

¹³ The annual spending on big data analytics will increase globally in the next three to five years by 24 percent in the life segment and by 27 percent in P&C segment (Müller et al., 2015).

¹⁴ For more detailed information on the tools, see, for example, SAS (2017) and Fayyad, Piatetsky-Shapiro, and Smyth (1996). In addition to traditional statistical methods, data mining uses machine learning algorithms, which iteratively learn from past computations, for more efficient analyses. Usually, machine learning algorithms are trained on existing data and then automatically analyze new data sets (Hall, Phan, & Whitson, 2016). Most commonly, for the analysis classification, clustering or regression algorithms are used (Fayyad et al., 1996). Machine learning algorithms are also used for applications which cannot be programmed

the use of big data raises legal and ethical questions. Politicians are now discussing whether insurers should be allowed to use all of the generated data for decision making, how long they may store the data, and which actions insurers must take to protect the data (e.g. against cyber-crime; Hussain & Prieto, 2016).¹⁵

A third obvious impact is that digitalization changes existing products (e.g., telematics insurance) and allows new product offerings (e.g., cyber risk insurance). Telematics devices are used in life/health and motor insurance to build smaller and more accurate risk-pools and offer cheaper prices to good risks.¹⁶ The sharing economy, i.e., lending or borrowing personal items for a short period, creates on-demand insurance markets where a premium is paid for the renting period (PWC, 2015). With respect to new offerings the notification requirements for data breaches in the U.S. have triggered the development of an insurance market for cyber risks, both in personal and commercial lines (Biener et al., 2015). The technological progress to date also makes it possible to underwrite risk which could not have been insured up to now.¹⁷ Furthermore, smart contracts—programs that automatically execute the claim payment under pre-defined conditions stored in the blockchain (Cant et al., 2016)—have the potential to be fully digital and fully automatic products. There are material differences when it comes to the impact on the value chain comparing different lines of business. The lines of business which are today most affected by digitalization are health insurance, motor insurance and home insurance. It seems that health insurance is a little ahead of other types of insurance, because of the large number of interactions a company has with the customers. Standardization and automatization of processes is much more efficiency-enhancing for health insurance compared with, for example, motor insurance, where the claim frequency on average is much lower. In motor insurance and home insurance we find manifold new technologies and innovative products (e.g., telematics insurance) that

by hand (e.g. handwriting recognition) or self-customizing problems (Amazon, Netflix product recommendations). The newly generated information can be used for applications such as risk allocation, customer segmentation, exploiting cross-selling potential, and fraud detection (Jones, 2016).

¹⁵ For example, the EU has reformed its data protection rules to simplify the use of big data for businesses and to set high standards of data protection (European Commission Justice, 2016). Furthermore, see Krotoszynski (2015) for a detailed comparison between the U.S. and EU legal systems regarding privacy rights.

¹⁶ For the discussion in motor insurance, we refer, e.g., to Paefgen et al. (2013), Filipova-Neumann and Welzel (2010) or Keller and Transchel (2016). Anchen, Frey, and Kirova (2015) present some thoughts on wearables for the life insurance market.

¹⁷ One example is the use of big data techniques for risk underwriting and analysis; Climate Corporation (US) uses climate and soil data to offer farmers insurance against losses from weather events (Müller et al., 2015). AllLife (South Africa) offers life and disability insurance to policyholders, who suffer from HIV or diabetes; in their monthly health checks, every client gets a personalized analysis and advice in managing their conditions. To assess their clients' conditions, the insurer has direct access to medical data from medical providers. If clients do not follow the check-up plan, coverage can be reduced or cancelled (Brat, Clark, Mehrotra, Stange, & Boyer-Chammond, 2014).

reduce the frequency of claims. The same also holds for health insurance with pay-as-you-live tariffs and the increasing use of gadgets that track customer behavior.

Table 3. Impact of digitalization on the insurer's value chain

<i>Value chain process</i>	<i>Tasks</i>	<i>Impact on the value chain</i>
Primary activities		
Marketing	• Market and customer research: researching ideas for product development. • Analyzing target groups. • Development of pricing strategy for product sales. • Designing of advertisement and communication strategies.	Big data: • More data resources for better customer segmentation. • Better calculation of the customer lifetime value and cross-selling potential. Video platforms: • Usage of videos for product explanations to (future) customer, company news, topics of asset management, regulations, etc. Website, social networks and messenger: • Product information/advertisement, reputation management.
Product development	• "Manufacturing" the products. • Product pricing (actuarial methods). • Check legal requirements.	Big data: • More and better data allow the insurer to reorganize the risk pools and apply a more risk-appropriate pricing. Internet of things: • New products focusing on prevention or situational insurance, e.g., travel insurance at hotel check-in. Blockchain: • Smart contracts, e.g., Fizzy by AXA.
Sales	• Customer acquisition, consultation. • Product sale. • After-sales.	Big data: • The CRM system can automatically be enriched with data from other data sources such as websites, etc. Cloud computing: • Contract information stored digitally. Chatbot and artificial intelligence: • Product sale can be automatically conducted via chatbot; for the customer, it is the same experience as chatting with a real human. Social networks and messenger: • New acquisition channels: messenger, social media. Video calls and mobile devices: • Sales location-independent through use of tablet, video calls, etc. Website and apps: • New information and sales channels, partly/fully automated. • Some process steps done by the customer (e.g. data input).
Underwriting	• Application handling. • Risk assessment. • Assessment of the final contract details, if necessary, ask for more information.	Artificial intelligence: • New possibilities for risk assessment, e.g., through image or language processing. Big data: • More data for risk assessment (reduction of information asymmetry, ex post and ex ante). Internet of things: • Telematics devices are used to get customers' data for risk and pricing calculation. Blockchain: • All information for automated underwriting is stored. Cloud computing: • Contract information stored digitally.

Table 3. Impact of digitalization on the insurer's value chain (continued)

<i>Value-chain process</i>	<i>Tasks</i>	<i>Impact on the value chain</i>
Contract administration/customer service	• Change of contract data. • Answering customer requests regarding the contract or other purposes.	Internet of things: • More responsibilities and tasks in the customer service process: fitness coaching, etc. Cloud computing: • Contract information stored digitally; can be changed by the customer (shift of the process). Chatbots and artificial intelligence: • Automated answering of service queries. Video calls, social networks, messenger and chat: • Video call or live chat for service questions.
Claim management	• Investigation of fraud. • Claim settlement.	Artificial intelligence and big data: • Prevention of fraud through data analytics. • Automated calculation and payout of the amount of damage. Blockchain: • Storage of the information for the automated payout. Mobile devices with apps: • Customers file their claims via smartphone.
Asset management	• Asset allocation. • Asset liability management.	Robo-advisor: • Automated asset management. Blockchain: • As a result of using one central database, transaction costs could decrease.
Risk management	• Analysis and management of all risks.	Artificial intelligence and big data: • Automated decision-making, e.g., for risk transfer or automated reporting.
Support activities		
General management	• Strategic planning and implementation of company goals.	Artificial intelligence: • Decision process supported by data analytics. • Internal processes are fully supported by digital possibilities (video calls, chats, cloud computing).
IT	• IT procurement (hard-/software) and installation. • IT service. • IT support. • IT development. • Coordination of IT processes.	Internet of things: • IT systems automatically report trouble and provide support to fix the problem. IT development: • Processes have to be more flexible and the "time to market" has to be shorter. • IT support via video calls and chats.
Human resources	• Planning HR development. • Job interviews. • Job market advertisement. • Job training.	• Usage of available media channels for recruitment. • Automated search for employees instead of outsourcing to recruitment companies. • Use of cloud computing for handling employees' and applicants' documents. • Using of video calls for employee training.
Controlling	• Data capture and analysis. • Reporting. • Business-KPI measurement.	• With digitized data, it will be easy to get automated reports. • Technology will enable interactive reporting (selection of reporting data), dynamic reporting and real-time planning.
Legal department	• Dealing with legal effects.	• New legal effects, e.g., data safety, privacy vs. transparency. • Software checks contracts automatically reducing basic and repetitive tasks.
Public relations	• Press/investor management.	• Shift from offline to online. • New communication channel: social media, messenger, etc.

3.3 Will the insurance industry lose parts of its value chain to other industries?

It has long been projected that like other industries, insurers will outsource major parts of their value chain to increase process efficiency (e.g., Haller, 1997). Maas and Bühler (2015), however, show that insurance managers still prefer to offer the full range of activities and not to specialize on parts of the value chain. But they also note that many insurers do not see IT development and IT operations as their core competence, which could lead to more outsourcing, if not done already, in this area.¹⁸ The change in the underwriting process due to full automatization could also lead to an outsourcing of the risk assessment process to companies that own the data, e.g., generated by telematic devices. This could be especially interesting for smaller players who do not have the resources for their own (technology) department. Moreover, customers are increasingly integrated in the value creation process: selected activities (e.g., change of personal data, reporting of claims) are done by the customer online, which is convenient for the customer, saves resources for the insurer, and therefore could lower premiums.

There is, however, an ongoing debate whether (on top of these decisions made by insurers themselves) the industry will be forced to give away parts of the value creation process and with this also parts of the profit margin to other industries. For example, the automobile industry could take over the sales and claim settlement processes. Given the high competition and decreasing margins in the automobile industry, automobile manufacturers are looking for additional profit margins in neighboring areas of their value chain.¹⁹ Their key advantage is access to the customer²⁰ and to the respective data. One scenario is that insurance products (e.g., product liability, car insurance, travel insurance) could be offered during the sales process by the producer (e.g., automobile manufacturer, technology provider) or retailer (e.g., Amazon), without any opportunities for insurers to intervene. Also, at later stages of the value chain other industries could get first access to information, for instance in the case of car accidents.

One question in this context is whether the producers and retailers are acting as brokers or as risk carriers. So far, most of these firms are acting as brokers, but if the margin of being a risk carrier is attractive enough and outweighed the broker margin, producers and retailers could also apply for a license and offer their own insurance products. The likelihood of doing this may be even higher for technology-driven firms like Amazon, Apple, Facebook or Google because they have huge amounts of relevant data and could

¹⁸ Maas and Bühler (2015) find that 42 percent of IT development and 51 percent of IT operations will be outsourced by 2020.

¹⁹ We can also observe the same behavior in the other direction, i.e., the increasing efforts of insurers to grow outside their core business. For example, Allianz recently bought the auto sales platform Instamotion Retail (Hegmann, 2016).

²⁰ The same arguments can be made for other industries, e.g., mobile phone providers.

profit from advantageous selection.²¹ It therefore seems plausible that the company with the access to the customer will absorb the majority of the profit margin.²² However, there are also reasons why technology firms or players from other industries may not be willing to enter the insurance market. It could be, for example, that a realistic return on equity for selling insurance is rather low and that technology firms like Apple have more attractive investment opportunities that offer higher returns.²³ Another factor is the large number of regulations for insurance companies; they serve as a barrier for new market entrants and consequently protect the established players. Another argument for not being a risk carrier could be the required expertise in different steps of the insurance value chain, which the players from other industries cannot build up without substantial upfront investments. Furthermore, as technology providers want to keep their customer retention on a high level, they may want to avoid negative headlines about their insurance business, for example due to rejected claims. Overall, the risk of disruption from other industries seems rather low at the moment, but this could change when new technologies emerge (see Section 4.1. for more discussion on this aspect).

3.4 Can insurtechs significantly disrupt the industry?

After some technology start-ups have left their footprints in the banking sector (e.g., Funding Circle, Prosper, Number26, Robinhood),²⁴ other start-ups are now concentrating on the insurance sector (so-called insurtechs). This can be seen by the amounts invested in insurtechs: the venture capital investments increased almost fivefold from 2014 to 2015, reaching USD 2.5 billion in 2015; the investment in the fintech market only doubled in the same interval (2014: USD 7.3 billion; 2015: USD 14.5 billion; KPMG & CBInsights, 2016). Comparing insurtechs to traditional insurers, Wiener and Theis (2017) argue that insurtechs may have systematic advantages by using the latest technology and being more flexible in their innovation processes. The existing insurtech start-ups can be divided into three categories: they offer specific services or

²¹ For example, technology firms offer payment solutions (e.g., Apple or Samsung Pay). Another example is Telefonica which offers a telematics motor insurance (O2 drive) in the U.K. However, it seems that Telefonica is not carrying the risk, but is rather an intermediary to other insurers. They are providing the customer with a telematics device.

²² We also refer to the valuation of companies like Google or Facebook, whose most valuable asset is the data of their customers.

²³ Note that the return on equity consideration does not only mean investing in other industries, but also working with the insurance industry with alternative business models. For example, Google has even withdrawn the insurance broker Google Compare from the U.S. and U.K. markets. One might suspect that the profit from pure advertisement on Google are higher than the potential profit from acting as a broker or risk carrier, all of which require substantial expertise and upfront investments (Jergler, 2016). Another example in this context is that both Amazon and Apple are working with insurance companies (London General Insurance Company Limited and AIG respectively) for their warranty programs Amazon protect and AppleCare+.

²⁴ For more examples, see KPMG and H2 Ventures (2015).

products to target: 1) customer experience (e.g., GetSafe, Backbase, Oscar); 2) business processes (e.g., Getsurance, Check24); or 3) new products (e.g., Trov, Metromile, Guevera).²⁵

In the category of customer experience, insurtechs take advantage of today's often analogue interactions between insurers and customers. For example, GetSafe offers an online administration tool for all contracts independent of the insurance company.²⁶ Backbase offers software to insurers to allow customers to track their application, view their contracts or message with a service representative. In the second category, business processes, insurtechs are typically active as aggregator platforms or they support claims handling. Aggregators create more transparency for customers but to make a profit customers have to purchase the products through their website. However, as we have argued before, most customers still purchase the products offline (Barwitz et al., 2016). Regarding claims handling, some insurtechs support the customer (e.g., RightIndem, Unfallfuchs) or even offer the entire process of claims management to insurers (e.g., Claimable). In the third category of new products, insurtechs typically focus on single products and do not offer the full spectrum of insurable risks. Some companies fill the gap for on-demand and sharing economy insurance (e.g., Trov, SafeShare), others use telematics devices for existing products (e.g., Metromile). Some insurtechs offer digital peer-to-peer insurance (e.g., Guevera, Friendsurance); if claims are low, money is paid back to the insured risk pool. Lemonade offers digital home insurance for a fixed fee, and if there is money left over it is given back to pre-defined charitable causes.

We see four arguments why it is rather unlikely that insurtechs will cause a disruption to the insurance industry. First, traditional insurance companies could easily copy the business model of insurtechs when it seems attractive. Second, instead of copying insurtechs, insurers could simply acquire them, because of their relatively small scale. We first saw this in the banking industry (e.g., BBVA acquired Simple and Holvi, Barclays acquired the LogicGroup), but in the meantime insurers have also invested in insurtechs (e.g., Wüstenrot & Württembergische acquisition of the financial assistant platform Treefin, Northwestern Mutual's acquisition of the financial planning platform LearnVest, Helvetia's acquisition of Moneypark). Third, it seems that insurtechs are more focused on cooperation than on rivalry with traditional insurers (Kottmann & Dördrechter, 2016). Especially partnerships with technology providers, such as big data analysis or blockchain technology, could save the insurance industry's resources. Fourth,

²⁵ We refer to Mesropyan (2016), Noack (2016), Kottmann and Dördrechter (2016) and Braun and Schreiber (2017) for more examples. We also refer to Braun and Schreiber (2017) for a more detailed discussion on the role of insurtechs, their business model, and how they could affect the insurance industry.

²⁶ We note that by using GetSafe the company is also contracted as the customer's broker. As a consequence, it is getting the trailer commission.

the amount of regulation, unsolved legal questions (e.g., consultant liability in online sales, data security), and lack of expertise could be a problem when insurtechs want to expand their businesses.²⁷

3.5 How does the insurability of risks change?

In Table 4, we summarize the expected insurability changes structured along Berliner's (1982) insurability criteria. We see three major effects: the effect of new information on information asymmetry and risk pooling, the implication of new technologies on loss frequency and severity, and the increasing dependencies through connectivity. Moreover, several legal and ethical questions arise.

The first influential effect on the insurability of risks could be access to information on customers through online texts, pictures and videos, via mobile phones and other devices (e.g., telematics devices). However, it is not clear if insurers will have access to these data. If individuals keep their personal risk assessment to themselves, this could increase adverse selection and, especially in the case of telematics insurance, it would not prevent moral hazard. If insurers are allowed to use the information on the individuals,²⁸ they will be able to form smaller homogenous risk pools.²⁹ As a consequence, good risks may pay a lower and bad risks a higher premium. In the health insurance segment, this debate is similar to the ongoing discussion on the use of genetic information for risk calculation. Hoy and Ruse (2005) argue that the reduction of adverse selection and therefore the increase in efficiency is accompanied by the effect that people who are in poor health are punished twice (higher premium as well as health problems) and that some people may refuse to take a genetic test because they are afraid that it would increase their insurance premium instead of seeing the test as a diagnostic instrument. Moreover, the authors argue that some people may not want to know their health condition, either because it could be hard to keep that information confidential or because they do not want to worry about their future health. Doherty and Posey (1998) find that for uninformed individuals a genetic test has a positive private value if prevention is sufficiently effective in lowering the premium, even though the information must be shared with the insurer.

²⁷ We emphasize that the reasons are outside of today's industry perspective. Examples from other industries (e.g., low-cost carriers in the airline industry) have shown the impact of a possible disruption that was not previously envisioned either.

²⁸ For example, health and life insurers could not only separate people by age and be whether they are smokers or non-smokers but, for instance, by how physically active they are. Another example is in motor insurance, where data are enriched with information about driving behavior (acceleration, braking behavior, speed, etc.).

²⁹ There is also a possibility that the customers share their information only with a technology provider (e.g. Apple tracks the usage behavior of their iPhone customers). In this constellation, the technology provider supplies the risk calculation and prevention. In exchange for carrying the risk, the insurers get a minimum margin.

Following on from this argument, we think that better data analysis methods and telematics insurance could be beneficial in all insurance segments, if individuals had the chance to emerge from bad risk classes by changing their behavior and/or taking preventive measures. For example, young drivers who are typically high-risk could reduce their insurance premiums if they drove carefully and their behavior was tracked by a telematics device. People who were overweight could get a discount when they reached a certain level of activity per day, which was tracked by the insurer. These tracking devices make efficient prevention measurable and risk insurable. For example, it could be determined if mold in a house had been caused by the tenants because they avoided regular airing or if it was a more general issue with the construction material. This access to more information and increasing transparency could also affect solidarity; better visibility of costs and benefits could reduce the willingness of good risks to subsidize the bad risks, especially in social insurance. The latter aspect and also the use of telematics devices in cases where people cannot change their behavior (e.g., genetic diseases) lead to open ethical questions which need to be answered in a societal dialogue.

Second, digitalization creates new machines and devices that influence loss frequency and severity. It is difficult to say if new innovations increase or decrease the average and maximum possible losses. On the one hand, automatization reduces the production costs of insured devices, such as medical instruments or automobiles. On the other hand, these devices could become more expensive because of all the new built-in technology. When looking at the health sector, one can see that technological innovations are one of the main cost drivers (Erixon & van der Marel, 2011). Regarding their internal processes, insurance companies could save administrative and production costs; moreover, by using technological devices they can reduce the loss probability and loss amount by incentivizing and controlling prevention measures.

A third effect is that an increasingly connected world could increase the maximum possible losses if risks cease to be independent, thereby reducing the insurability of risks. For example, Biener et al. (2015) analyze the insurability of cyber risks and show that one major hurdle is the accumulation risk. Given that all individuals and companies are using the same software and systems, increasing the diversity of software products and IT systems could be beneficial from an insurability perspective.

Table 4. Impact of digitalization on insurability of risks (Berliner, 1982)

<i>Insurability criteria</i>	<i>Valuation</i>	<i>Assessment</i>	
Actuarial	(1) Randomness of loss occurrence	Because of the IoT and big data, smaller risk pools can be created, which will lead to a more distinguished separation of risks. Still, the loss occurrence in each risk pool is random.	Does not contradict insurability.
	(2) Maximum possible loss	The “connected world” could lead to higher losses if one component fails. As data storage becomes an important asset, losses from cybercrime could rise.	Identification of maximum loss more problematic.
	(3) Average loss per event	- On the one hand, the digitalization will reduce administration and production costs for insurers. On the other hand, insured objects are getting more expensive with all built in technology (higher loss amount). - Prevention could help to reduce the average costs.	Hard to verify if the average will decrease or increase
	(4) Loss exposure	- The size of the risk pools has to be adequate so that the insurer can calculate the loss probability. - Loss probability could be reduced through technical assistance systems or IoT, e.g., in motor or theft insurance.	Does not contradict insurability.
	(5) Information asymmetry	Depending on regulation and willingness to share personal information, asymmetries could become smaller or larger.	Depends on the regulation.
Market	(6) Insurance premium	Through smart data and IoT insurers could improve the accuracy of their pricing. Good risks could get a premium reduction. Bad risks could pay more.	Overall, costs and thus premiums could decrease.
	(7) Cover limits	Because of big data methods and artificial intelligence, the loss amount could be better predicted, which might affect the selection of cover limits.	Does not contradict insurability.
Society	(8) Public policy	- The ethical questions that arise are similar to the ongoing debate on genetic tests. - If individuals have the chance to emerge from bad risk classes by changing their behavior and/or taking preventive measures, the new measures could be beneficial. If not, ethical questions could arise. - Increased transparency could affect solidarity; better visibility of costs and benefits could reduce the willingness of good risks to subsidize bad risks. - Willingness to share information and to use telematics devices needs to be discussed.³⁰	Does not contradict insurability, but ethical aspects have to be discussed.
	(9) Legal restrictions	- The increasing transparency raises legal questions, e.g., can individuals be discriminated against because of their health conditions (e.g., in social insurance)? - Regarding the use of data, other legal questions exist: Is the collection of data in line with current freedom and equal rights?³¹ Who is allowed to use the data? What has to be done regarding data quality and security? - Also, in the area of autonomous driving, in addition to the ongoing debate on ethical questions (e.g., should an algorithm decide if the driver gets hurt or another person)³², legal questions arise regarding liability (manufacturer vs. software developer vs. driver).	Does not contradict insurability, but legal questions have to be discussed.

³⁰ There are differences in the willingness to share private information depending on the area of life (car, housing or health) and country. The majority of people would use a GPS transmitter to locate a stolen car or sensors in the house for fire detection but would not want to share health conditions (Maas, Graf, & Bieck, 2008).

³¹ Also, see Nationaler Ethikrat Germany (2007).

³² For example, see Kolmar and Booms (2016).

4 Derivation of potential future work

Table 5 summarizes the results for the five core topics discussed in Section 3. Based on these results, we now derive potential areas of future work from both an academic and a practical perspective.

Table 5. Summary of results

1. What is digitalization and which technologies will influence the industry?
• Digitalization is the integration of the analogue and digital worlds with new technologies that enhance customer interaction, data availability, and business processes. • The relevant technologies are in the fields of data acquisition and analysis (artificial intelligence, big data, IoT), data storage (blockchain, cloud computing) and communication (apps, chatbots, robo-advisor, webpages, social networks, messenger, video calls, video platforms).
2. What is the impact of these technologies on the value chain?
• Digitalization changes the way insurers and customer interact (e.g., sales, customer service). • Digitalization and automatization influence all business processes (e.g., automated processing of contracts) and the decision-making process, including the risk assessment (e.g., automated underwriting with artificial intelligence and big data). • Digitalization changes existing products (e.g., telematics insurance) and allows new product offerings (e.g., cyber risk insurance).
3. Will the insurance industry lose parts of their value chain to other industries?
• Companies from other industries may have a better access to the customer or the respective data, but at the moment it seems unlikely they will take over substantial parts of the insurance value chain; this is because a realistic return on equity is too small to justify investments and because more attractive alternatives exist (investments in other businesses, cooperation with insurers); moreover, regulation and lack of expertise serve as entry barriers. • Statement only holds for today but may not in the future (see Section 4.1).
4. Can insurtechs significantly disrupt the industry?
• It seems rather unlikely that insurtechs will cause a major change or disruption to the insurance industry (today and in the future). • Reasons: Business model of insurtechs can be easily copied, insurers could easily acquire small insurtechs, insurtechs are focused more on cooperation than rivalry with traditional insurers; regulation and lack of expertise serve as entry barriers when insurtechs want to expand their businesses.
5. How does the insurability of risks change?
• New information impacts information asymmetry (depending on who has access to the customer data) and risk pools, which will become smaller and more homogeneous. • New technologies change loss frequency and severity (production and administrations costs could decrease, but insured values could increase due to costlier built-in technology); new technologies could also increase dependences through connectivity (cyber risks). • Manifold legal and ethical questions arise (Which information should be used? Who is liable?).

4.1 What should the insurance industry do in response to digitalization?

If we consider all of the above discussions from a customer point of view, it seems that digitalization has great potential to increase customer value by offering better products at lower prices. Furthermore, with better risk calculation and data, insurance companies could consult their customers regarding prevention measures, e.g., warning a car driver in dangerous situations and thus reducing the number of claims. However, as long as the pooling of risks and the realization of diversification in that pooling is not seriously affected by the digital transformation, the traditional insurance idea is not in question.³³

³³ We note that better prevention could reduce loss probability and loss amount so much that the utility gain from transferring the risk is not enough to justify the transaction costs of an insurance company. Then the idea of

The relevant question is more how to optimally organize this risk pooling. Should they do this as integrated service companies that do the major part of the value creation by themselves, or in another, maybe less centralized way? At the time of writing, the risk of losing major parts of the value chain to other industries seems rather low. But this could change quickly with new technologies. For example, when mobile devices pervade every aspect of daily life, users seeking convenience may allow companies like Apple to use this information to optimize their life. In such a scenario, the mobile device could offer relevant data to third parties to identify optimized offerings, for example, for insurance. Such an endeavor could greatly benefit customer value, but the implications for product variety and competition are highly unclear. For this reason, it is imperative that insurance companies follow the technological developments closely and seek collaboration to learn from technology companies and build up the requisite skills. One example is the ability to adapt to digital change which must be further developed. This is relevant, because most insurance companies are working in part with old IT systems and need further investments to prepare people and systems for the digital world. Moreover, insurers need to define the future work environment for their employees and sales representatives (sales process, sales tools, etc.). But the core idea of insurance—a risk-adequate calculation and the pooling of risk—remains.

There are several questions that insurance practitioners need to answer about digitalization. Regulators must define how and where they have to intervene. For example, to what extent should insurtechs be regulated? Which data should insurance companies be allowed to use (which raises the ethical questions outlined in Section 3.5)? Another question is how insurers should set priorities because they cannot concentrate on all digitalization topics equally. In this context, Maas and Bühler (2015) identify, based on the concept from Treacy and Wiersema (1995), three strategic pathways: customer intimacy, operational excellence, or product leadership, exactly reflecting these categories of impact.³⁴ A related question is how to organize the integration of new technologies and innovative models in an organization (e.g., Burgelman, Christensen, & Wheelwright, 2008, present the latest research on technology management); many insurance companies operate their own incubators (e.g., Lumenlab,

insurance would be in question. We see this, however, as a rather extreme scenario, which is not going to be realized for at least the next ten years. But customers prefer the accident that never happens, i.e. digitization will lead insurers to move toward mitigation and prevention.

³⁴ Müller et al. (2015) argue in the same direction by introducing four strategic pathways: advanced analyzer, digital distributor, customer-centric insurer, and effective operator. Johansson and Vogelgesang (2015) predict that the digital transformation will also impact the workforce of insurance companies; insurers will need to attract new employees with knowledge in data science, analytics, and/or IT-development. Moreover, there will be a significant number of layoffs in the operations department.

Allianz X, Werk 1) or cooperate with insurtechs, but empirically it is not clear which model works better.

On the technical side, an open question about digitalization is whether the benefits outweigh the investments in IT and people (e.g., when specific investments for better risk calculation, fraud detection or new insurance products are evaluated). Also, the blockchain technology seems attractive, given that it could fully automatize insurance offerings, but the barriers to and limitations of implementing such models still need to be explored. It is worth mentioning that not every question needs to be answered by each company; some can be addressed collaboratively. The analysis of the general implications of new technologies (e.g., blockchain or internet of things) on insurers are good examples.

If an insurance company wants to survive into the next decades, not to invest in new technology may not seem a realistic option, but in principal it could also be an option to send (parts of) the existing company into a controlled run-off and let the future digital business be done by new divisions that are developed from scratch without legacy systems. We believe that, especially from a regulatory perspective such a scenario should be discussed, because digitalization could trigger a lot of consolidation within the industry.

4.2 What future academic research is needed?

So far there has been little academic research on digitalization in the insurance segment. This seems surprising, given that digitalization and big data offer enormous potential for empirical research. One example is the increasing use of telematics devices in motor insurance. How does telematics insurance affect driving behavior? If a risk reduction can be observed empirically, is it a result of less moral hazard or of adverse selection? How can we separate the two? To our knowledge, the few academic studies that exist have not analyzed empirically the impact of telematics insurance on both moral hazard and adverse selection.³⁵

The identification and evaluation of big data techniques and artificial intelligence opens up a new research field, for example, from the perspective of actuarial science (pricing telematics contracts). The use of such information creates a space for legal and ethical questions that have not yet been answered in academia. If in the future large technology firms like Apple or Google gain access to a lot of information, how will they use it? What is the role of insurance companies in such a world? We refer to the discussion on how mobile devices could track every aspect of daily life and the implications for

³⁵ Filipova-Neumann and Welzel (2010) develop a model for telematics motor insurance demand. Other studies focus on the impact of assistance systems or financial incentives on driving behavior, e.g., Hummel, Kühn, Bende, and Lang (2011) or Bolderdijk, Knockaert, Steg, and Verhoef (2011).

product variety and competition. In general, more research is needed to analyze how privacy and data protection laws interact with big data applications.

Regarding future research, the role of the insurance industry in insuring the risks from the digital world is noteworthy. For example, can the availability of cyber risk insurance facilitate investments in cyber risk management? How can modelling and pricing of cyber risk be improved, given the lack of data, dynamic changes in risk characteristics, and complex correlation structures? Are transfer schemes to the capital market (alternative risk transfer instruments such as insurance linked securities) a viable solution to provide risk-bearing capacity for cyber risk to develop the cyber risk insurance market?

In general, the link between new technologies and insurance will raise many new research questions. For example, what should liability insurance look like in the context of self-driving cars? What does pay-as-you-live mean for the insurance idea of providing solidarity? What if the risk profile is fully known to the insurance company? And what if mitigation and prevention reduce the loss exposure so much that the idea of insurance becomes redundant (i.e. the utility gain from risk transfer is too small to justify the transaction costs)? All these questions may seem a little far away, but researchers may want to think about such scenarios and their consequences for the economy and society today. We believe that the academic community should also be part of the discussion on how to use digital technologies in economy and society.

References

- Allianz (2016). Blockchain technology successfully piloted by Allianz Risk Transfer and Nephila for catastrophe swap. Retrieved from <http://www.agcs.allianz.com/about-us/news/blockchain-technology-successfully-piloted-by-allianz-risk-transfer-and-nephila-for-catastrophe-swap-/>, accessed on 11 January 2017.
- Anchen, J., Frey, A., & Kirova, M. (2015). Life insurance in the digital age: fundamental transformation ahead. Swiss Re sigma. Retrieved from http://media.swissre.com/documents/sigma6_2015_en.pdf, accessed on 26 January 2017.
- Back, A., Berghaus, S., & Kaltenrieder, B. (2016). Digital maturity and transformation report 2016. IWI-HSG and Crosswalk. Retrieved from <https://crosswalk.ch/dmtr2016>, accessed on 15 December 2016.
- Barwitz, N., Maas, P., Block, D., & Nützenadel, C. (2016). Die Customer Journey in einer multioptionalen Welt. I.VW-HSG and Synpulse Schweiz AG. Retrieved from <http://www.ivw.unisg.ch/~media/internet/content/dateien/instituteundcenters/ivw/studien/pm-customer%20journey%20mfz-studie2016.pdf>, accessed on 24 January 2017.
- Bauer, A., Gröninger, Y., Scheidt, J., Garcia, R., & Rimpo, E. (2016). Dying, surviving or thriving: strategic analysis of the future Swiss insurance market. EY. Retrieved from <https://swissfinte.ch/wp-content/uploads/2016/07/dying-surviving-or-thriving-english-study-1.pdf>, accessed on 03 October 2016.
- Berger, D., Broer, P., & Pankoke, D. (2016). Digitization in life insurance: A prerequisite for success in spite of low interest rates. I.VW-HSG Trendmonitor, 1, 15–19.
- Berliner, B. (1982). Limits of insurability of risks. Englewood Cliffs, NJ: Prentice-Hall.
- Bieck, C., Marshall, A., & Patel, S. (2014). Digital reinvention: trust, transparency and technology in the insurance world of tomorrow. IBM Institute for Business Value. Retrieved from <https://public.dhe.ibm.com/common/ssi/ecm/gb/en/gbe03589usen/GBE03589USEN.PDF>, accessed on 22 February 2017.
- Bieck, C., & Tjioe L.-H. (2015). Capturing hearts, minds and market share: how connected insurers are improving customer retention. IBM Institute for Business Value. Retrieved from <https://www-935.ibm.com/services/us/gbs/thoughtleadership/insuranceretention/>, accessed on 22 February 2017.
- Biener, C., & Eling, M. (2012). Insurability in microinsurance markets: an analysis of problems and potential solutions. *Geneva Papers on Risk and Insurance – Issues and Practice*, 37(1), 77–107.
- Biener, C., Eling, M., & Wirfs, J. H. (2015). Insurability of cyber risk: an empirical analysis. *Geneva Papers on Risk and Insurance – Issues and Practice*, 40(1), 131–158.
- Bitkom, & KPMG (2016). Mit Daten Werte schaffen. Retrieved from <https://cdn2.hubspot.net/hubfs/571339/LandingPages-PDF/kpmg-mdws-201-sec.pdf>, accessed on 28 February 2017.

- Bolderdijk, J. W., Knockaert, J., Steg, L., & Verhoef, E. (2011). Effects of pay-as-you-drive vehicle insurance on young drivers' speed choice: results of a Dutch field experiment. *Accident analysis and prevention*, 43(3), 1181–1186.
- Brat, E., Clark, P., Mehrotra, P., Stange, A., & Boyer-Chammard, C. (2014). Bringing big data to life: four opportunities for insurers. The Boston Consulting Group. Retrieved from https://www.bcgperspectives.com/content/articles/insurance_digital_economy_bringing_big_data_life/, accessed on 27 January 2017.
- Braun, A., & Schreiber, F. (2017). The current insurtech landscape: business models and disruptive potential. I.VW-HSG. Retrieved from http://www.ivw.unisg.ch/~media/internet/content/dateien/instituteundcenters/ivw/studien/ab-insurtech_2017.pdf, accessed on 16 May 2017.
- Breading, M (2012). The drive to digitization in insurance: turning “big paper” into big profit. SMA. Retrieved from <http://www.the-digital-insurer.com/wp-content/uploads/2014/05/183-The-Drive-to-Digitization-in-Insurance.pdf>, accessed on 03 October 2016.
- Burgelman, R., Christensen, C., & Wheelwright, S. (2008). Strategic management of technology and innovation (5 ed). McGraw-Hill/Irwin.
- Cant, B., Khadikar, A., Ruiter, A., Bronebakk, J. B., Coumaros, J., Buvat, J., & Gupta, A. (2016). Smart contracts in financial services: getting from hype to reality. Capgemini Consulting. Retrieved from <https://www.capgemini-consulting.com/resource-file-access/resource/pdf/smart-contracts.pdf>, accessed on 26 January 2017.
- Cash (2016). Helvetia übernimmt 70% am Hypothekenvermittler Moneypark. Retrieved from <https://www.cash.ch/news/boersenticker-firmen/helvetia-ubernimmt-70-am-hypothekenvermittler-moneypark-522954>, accessed on 11 January 2017.
- Catlin, T., Hartmann, R., Segev, I., & Tentis, R. (2015). The making of a digital insurer: the path to enhanced profitability, lower costs and stronger customer loyalty. McKinsey & Company. Retrieved from <http://www.mckinsey.com/industries/financial-services/our-insights/the-making-of-a-digital-insurer>, accessed on 03 October 2016.
- Catlin, T., McGranahan, D., & Ray, S. (2013). Winning share and customer loyalty in auto insurance, McKinsey & Company. Retrieved from <https://de.scribd.com/document/306175438/Winning-Share-and-Customer-Loyalty-in-Auto-Insurance>, accessed on 22 February 2017.
- Chathoth, P. (2007). The impact of information technology on hotel operations, service management and transaction costs: a conceptual framework for full-service hotel firms. *International Journal of Hospitality Management*, 26(2), 395–408.
- Chester, A., Clarke, R., & Libarikian (2016). Transforming into an analytics-driven insurance carrier. McKinsey & Company. Retrieved from <http://www.mckinsey.com/industries/financial-services/our-insights/transforming-into-an-analytics-driven-insurance-carrier>, accessed on 03 October 2016.

- Crosby, M., Nachiappan, Pattanayak, P., Verma, S., & Kalyanaraman, V. (2016). Blockchain technology: beyond bitcoin. *Applied Innovation Review* 2. Retrieved from <http://scet.berkeley.edu/wp-content/uploads/AIR-2016-Blockchain.pdf>, accessed on 17 January 2017.
- Doherty, N., & Posey, L. (1998). On the value of a checkup: adverse selection, moral hazard and the value of information. *Journal of Risk and Insurance*, 65(2), 189–211.
- Dörner, K., & Edelman, D. (2015). What ‘digital’ really means. McKinsey & Company. Retrieved from <http://www.mckinsey.com/industries/high-tech/our-insights/what-digital-really-means>, accessed on 15 December 2016.
- Eling, M., & Schnell, W. (2016). What do we know about cyber risk and cyber risk insurance? *Journal of Risk Finance*, 17(5), 474–491.
- Erixon, F., & van der Marel, E. (2011). What is driving the rise in health care expenditures? An inquiry into the nature and causes of the cost disease. ECIPE working paper 5.
- European Commission Justice (2016). Protection of personal data. Retrieved from http://ecF.europa.eu/justice/data-protection/index_en.htm, accessed on 18 January 2017.
- Fayyad, U., Piatetsky-Shapiro, G., & Smyth, P. (1996). From data mining to knowledge discovery in databases. *AI Magazine*, 17(3), 37–54.
- Filipova-Neumann, L., & Welzel, P. (2010). Reducing asymmetric information in insurance markets: cars with black boxes. *Telematics and Informatics*, 27(4), 394–403.
- Finaccord (2013). Aggregation metrics: consumer approaches to insurance comparison sites in Europe. Retrieved from http://www.finaccord.com/press-release_2013_aggregation-metrics_consumer-approaches-to-online-insurance-comparison-sites-in-europe_channels-used-to-buy-insurance.htm, accessed on 17 January 2017.
- Gandomi, A., & Haider, M. (2014). Beyond the hype: Big data concepts, methods, and analytics. *International Journal of Information Management*, 35, 137–144.
- Hall, P., Phan, W., & Whitson, K. (2016). The evolution of analytics: opportunities and challenges for machine learning in business. Sebastopol, CA: O'Reilly Media.
- Haller, M. (1997). Von Assekuranz 2000 zur Versicherung im Netzwerk 2.007. I.VW-HSG. Retrieved from http://www.risiko-dialog.ch/images/RD-Media/PDF/Team/Publikationen_MH/1997-01_von_assekuranz_2000_zur_versicherung_im_netzwerk_2_007.pdf, accessed on 26 October 2016.
- Hegmann, G. (2016). Allianz wird zum Amazon des Gebrauchtwagenhandels. Die Welt. Retrieved from <https://www.welt.de/wirtschaft/article158841373/Allianz-wird-zum-Amazon-des-Gebrauchtwagen-handels.html>, accessed on 10 April 2017.
- Hiendlmeier, S., & Hertting, M. (2015). The impacts of digitization on the management of insurance companies: steering business in a digital world. Horváth & Partners. Retrieved from https://www.horvath-partners.com/fileadmin/horvath-partners.com/assets/05_Media_Center/PDFs/englisch/WP_Insurance_Digital_web_g.pdf, accessed on 03 October 2016.

- Hoy, M., & Ruse, M. (2005). Regulating genetic information in insurance markets. *Risk Management and Insurance Review*, 8(2), 211–237.
- Huckstep, R. (2017). Chatbot and the rise of the automated insurance agent. Retrieved from <http://www.the-digital-insurer.com/blog/insurtech-the-rise-of-the-automated-insurance-agent-aka-the-insurtech-chatbot/>, accessed on 18 January 2017.
- Hummel, T., Kühn, M., Bende, J., & Lang, A. (2011). Advanced driver assistance systems: an investigation of their potential safety benefits based on an analysis of insurance claims in Germany. German Insurance Association – Research Report FS 03.
- Hussain, K., & Prieto, E. (2016). Big data in the finance and insurance sectors. In J. M. Cavanillas, E. Curry and W. Wahlster (Ed.), *New Horizons for a data-driven economy – a roadmap for usage and exploitation of Big Data in Europe* (209–223). Retrieved from <http://link.springer.com/book/10.1007%2F978-3-319-21569-3>.
- Ingleton, R., Ozler, Y., & Thomas, P. (2011). The digitization of everything: how organizations must adapt to changing consumer behavior. EY. Retrieved from http://www.ey.com/Publication/vwLUAssets/The_digitisation_of_everything_-_How_organisations_must_adapt_to_changing_consumer_behaviour/%24file/EY_Digitisation_of_everything.pdf, accessed on 03 October 2016.
- Jergler, D. (2016). Insurance industry analyzes Google's failed online insurance experiment, *Insurance Journal*. Retrieved from <http://www.insurancejournal.com/news/national/2016/02/23/399632.htm>, accessed on 24 February 2017.
- Johansson, S., & Vogelgesang, U. (2015). Insurance on the threshold of digitization: implications for the life and p&c workforce. McKinsey & Company. Retrieved from <http://www.mckinsey.com/industries/financial-services/our-insights/insurance-on-the-threshold-of-digitization>, accessed on 03 October 2016.
- Jones, M. (2016). Anything you can do, AI can do better: machine learning and artificial intelligence in insurance. *Insurance Nexus*. Retrieved from <http://www.insurancenexus.com/analytics/anything-you-can-do-ai-can-do-better-machine-learning>, accessed on 24 January 2017.
- Kane, G., Palmer, D., Phillips, A., Kiron, D., & Buckley, N. (2015). Strategy, not technology, drives digital transformation – becoming a digitally mature enterprise. MIT Sloan Management Review and Deloitte. Retrieved from <http://sloanreview.mit.edu/projects/strategy-drives-digital-transformation>, accessed 20 December 2016.
- Keller, A., & Transchel, F. (2016). Telematics: connecting the dots. *Swiss Re*. Retrieved from http://www.swissre.com/library/archive/Telematics_connecting_the_dots.html, accessed on 26 January 2017.
- Kolmar, M., & Booms, M. (2016). Autonome Autos: Keine Algorithmen für ethische Fragen. *Neue Zürcher Zeitung*. Retrieved from <https://www.nzz.ch/meinung/kommentare/keine-algorithmen-fuer-ethische-fragen-ld.4483>, accessed on 27 February 2017.

- Kottmann, D., & Dördrechter, N. (2016). Zukunft von Insurtech in Deutschland – Der Insurtech Radar. Oliver Wyman and Policen Direkt. Retrieved from http://www.oliverwyman.de/content/dam/oliver-wyman/europe/germany/de/insights/publications/2016/jul/Oliver_Wyman_Policen%20Direkt_Insurtech-Radar.pdf, accessed on 03 October 2016.
- KPMG, & H2 Ventures (2015). Fintech 100: leading global fintech innovators report 2015. Retrieved from <http://fintechnews.ch/fintech/top-10-fintech-startups/2454/>, accessed on 01 February 2017.
- KPMG, & CBInsights (2016). The pulse of fintech Q2 2016: global analysis of fintech venture funding. Retrieved from <https://home.kpmg.com/xx/en/home/insights/2016/11/the-pulse-of-fintech-q2-2016.html>, accessed on 01 February 2016.
- Krotoszynski, R. J. Jr. (2015). Reconciling privacy and speech in the era of big data: a comparative legal analysis. *William and Mary Law Review*, 56(4), 1279–1338.
- Levy, F., & Murnane, R. (2005). The new division of labor: how computers are creating the next job market. Princeton: Princeton University Press.
- Maas, P., & Bühler, P. (2015). Industrialisierung der Assekuranz in einer digitalen Welt. I.VW-HSG and Adcubum St. Gallen. Retrieved from <http://www.ivw.unisg.ch/~media/internet/content/dateien/instituteundcenters/ivw/studien/industrialisierung-digital2015.pdf>, accessed on 03 October 2016.
- Maas, P., Graf, A., & Bieck, C. (2008). Trust, transparency and technology: European customers' perspectives on insurance and innovation. I.VW-HSG and IBM institute for business value. Retrieved from <https://www-935.ibm.com/services/us/gbs/bus/pdf/gbe03008-usen-02-insurancet3.pdf>, accessed on 22 February 2017.
- McCarthy, J. (2007). What is artificial intelligence? Retrieved from <http://www-formal.stanford.edu/jmc/whatisai.pdf>, accessed on 05 September 2017.
- McCurry, J. (2017). Japanese company replaces office workers with artificial intelligence. The Guardian. Retrieved from <https://www.theguardian.com/technology/2017/jan/05/japanese-company-replaces-office-workers-artificial-intelligence-ai-fukoku-mutual-life-insurance>, accessed on 17 January 2017.
- Mesrobian, E. (2016). 101 insurtech startups revolutionizing the \$4.5-Trillion-Dollar insurance industry. Retrieved from <https://letstalkpayments.com/101-insurtech-startups-revolutionizing-the-4-5-trillion-dollar-insurance-industry/>, accessed on 01 February 2017.
- Moneta, A. (2014). The customer-centric insurer in the digital era. Accenture. Retrieved from https://www.accenture.com/t20150523T033833__w__/sg-en/_acnmedia/Accenture/Conversion-Assets/DotCom/Documents/Global/PDF/Dualpub_9/Accenture-The-Customer-Centric-Insurer-In-The-Digital-Era.pdf, accessed on 03 October 2016.
- Moreau, F. (2013). The disruptive nature of digitization: the case of the recorded music industry. *International Journal of Arts Management*, 15(2), 18–31.

- Müller, F., Naujoks, H., Singh, H., Schwarz, G., Schwedel, A., & Thomson, K. (2015). Global digital insurance benchmarking report 2015. Bain & Company. Retrieved from <http://www.bain.com/Images/GLOBAL-DIGITAL-INSURANCE-2015.pdf>, accessed on 03 October 2016.
- Nationaler Ethikrat Deutschland (2007). Prädikative Gesundheitsinformationen bei Einstellungsuntersuchungen: Stellungnahme. Retrieved from <http://www.ethikrat.org/dateien/pdf/paediktive-gesundheitsinformationen-bei-einstellungsuntersuchungen.pdf>, accessed on 27 February 2017.
- Naujoks, H., Schwarz, G., Matouschek, G., & von Hülsen, B. (2013). Versicherungen: Die digitale Herausforderung. Bain & Company. Retrieved from http://www.bain.de/Images/BainBrief_Versicherungen_Die-digitale-Herausforderung_FINAL.pdf, accessed on 03 October 2016.
- Naujoks, H., & Sherer, L. (2016). How insurers can invest in big data analytics to improve decision making. Bain & Company. Retrieved from http://www.bain.com/Images/bain_brief_Insurance_Analytics.pdf, accessed on 03 October 2016.
- Naydenov, R., Liveri, D., Dupre, L., & Chalvatzi, E. (2015). Secure use of cloud computing in the finance sector. European Union Agency for Network and Information Security. Retrieved from <https://www.enisa.europa.eu/publications/cloud-in-finance>, accessed on 03 October 2016.
- Noack, S., & Illguth, V. (2016). Insurtech Übersicht DACH. New Players Network. Retrieved from <http://newplayersnetwork.jetzt/wp-content/uploads/2016/05/InsurTechs-2016-DACH.pdf>, accessed on 03 October 2016.
- Paefgen, J., Fleisch, E., Ackermann, L., Staake, T., Best, J., & Egli, L. (2013). Telematics strategy for automobile insurers. I-Lab Whitepaper. Retrieved from [https://www.alexandria.unisg.ch/223402/1/Telematics%20Strategy%20for%20Automobile%20Insurers%20\(I-Lab%20Whitepaper\).pdf](https://www.alexandria.unisg.ch/223402/1/Telematics%20Strategy%20for%20Automobile%20Insurers%20(I-Lab%20Whitepaper).pdf), accessed on 17 January 2017.
- Pain, D., Tamm, K., & Turner, G. (2014). Digital distribution in insurance: a quiet revolution. Swiss Re sigma 2/2014. Retrieved from http://media.swissre.com/documents/sigma2_2014_en.pdf, accessed on 17 January 2017.
- Porter, M. (1985). The competitive advantage: creating and sustaining superior performance, The Free Press, New York.
- PWC (2015). The sharing economy. Consumer Intelligence Series. Retrieved from <http://www.pwc.com/us/en/industry/entertainment-media/publications/consumer-intelligence-series/assets/pwc-cis-sharing-economy.pdf>, accessed on 26 January 2017.
- PWC (2016). AI in insurance: hype or reality? Retrieved from <https://www.pwc.com/us/en/insurance/publications/assets/pwc-top-issues-artificial-intelligence.pdf>, accessed on 05 September 2017.
- Rahlfs, C. (2007). Redefinition der Wertschöpfungskette von Versicherungsunternehmen. Gabler Edition Wirtschaft. Wiesbaden: Deutscher Universitäts-Verlag.

- Salcedo-Sanz, S., Cuadra, L., Portilla-Figueras, A., Jiménez-Fernández, S., & Alexandre, E. (2013). A review of computational intelligence algorithms in insurance applications. In: *Statistical and Soft Computing Approaches in Insurance Problems*. Nova Science Publishers, Inc. Commack, NY.
- SAS (2017). Data mining – what it is and why it matters. Retrieved from http://www.sas.com/en_us/insights/analytics/data-mining.html, accessed on 25 January 2017.
- Stephenson, D. (2013). 7 big data techniques that create business value. Retrieved from <https://www.firmex.com/thedealroom/7-big-data-techniques-that-create-business-value/>, accessed on 18 January 2017.
- Swiss Re (2016). Insurers and reinsurers launch blockchain initiative. Retrieved from http://www.swissre.com/reinsurance/insurers_and_reinsurers_launch_blockchain_initiative.html, accessed on 11 January 2017.
- Tischhauser, P., Naumann, M., Candreia, A., Treier, S., & Senser, J. (2016). Digitalisierung: Der Schweizer Versicherungssektor im Umbruch. The Boston Consulting Group. Retrieved from http://image-src.bcg.com/BCG_COM/Report_Digitalisierung_tcm20-40440.pdf, accessed on 03 October 2016.
- Treacy, M., & Wiersema, F. (1995). *The discipline of market leaders: choose your customer, narrow your focus, dominate your market*. Massachusetts: Addison-Wesley Pub. Co.
- Wiener, K., & Theis, A. (2017). InsurTech(s): Zwischen Konkurrenz und Partnerschaft. GDV – Makro und Märkte kompakt 9. Retrieved from <http://www.gdv.de/2017/02/schumpeterscher-moment-fuer-die-versicherungsbranche/>, accessed on 27 February 2017.
- Zurich, GfK, & Google (2016). ROPO Studie für Versicherungsprodukte in Deutschland – Kernergebnisse. Retrieved from <https://www.zurich.de/de-de/ueber-uns/presse/aktuell/gfk-studie>, accessed on 17 January 2017.

Appendix A Dataset of papers and industry studies

Table A. Dataset of papers and industry studies

<i>Title</i>	<i>Author(s)</i>	<i>Year</i>	<i>Journal/Book</i>	<i>Vol.</i>	<i>No.</i>	<i>Pages</i>	<i>Country</i>
Computational methods							
A review of computational intelligence algorithms in insurance applications.	Sancho Salcedo-Sanz Lucas Cuadra Portilla-Figueras, A Silvia Jiménez-Fernández Enrique Alexandre	2013	Statistical and Soft Computing Approaches in Insurance Problems				no specific
Customer survey							
Aggregation metrics: consumer approaches to insurance comparison sites in Europe	unknown	2013	Press release (Finaccord)				Europe
Capturing hearts, minds and market share: how connected insurers are improving customer retention	Christian Bieck Lee-Han Tjioe	2015	Industry study (IBM)				no specific
Die Customer Journey in einer multiptionalen Welt	Niklas Barwitz Peter Maas Dennis Block Christoph Nützenadel	2016	Industry study (I.VW-HSG and Synpulse)				Germany, Switzerland, Austria
ROPO Studie für Versicherungsprodukte in Deutschland – Kernergebnisse	unknown	2016	Industry study (Zurich, GfK and Google)				Germany
Trust, transparency and technology: European customers' perspectives on insurance and innovation	Peter Maas Albert Graf Christian Bieck	2008	Industry study (I.VW-HSG and IBM)				Denmark, Netherlands, France, U.K., Germany, Switzerland U.S.
Winning share and customer loyalty in auto insurance	Tangy Catlin Devin McGranahan Sharmila Ray	2013	Industry study (McKinsey & Company)				
Insurability							
Digitales Monitoring: Fluch oder Segen?	Hato Schmeiser Lukas Reichel	2016	I.VW-HSG Trendmonitor		3	3–5	Germany, Switzerland, Austria
Harnessing technology to narrow the insurance protection gap	Kai-Uwe Schanz Fabian Sommerrock	2016	Industry study (The Geneva Association)				no specific
Insurability in microinsurance markets: an analysis of problems and potential solutions	Christian Biener Martin Eling	2012	The Geneva Papers on Risk and Insurance	37	1	77–107	no specific

Table A. Dataset of papers and industry studies (continued)

<i>Title</i>	<i>Author(s)</i>	<i>Year</i>	<i>Journal/Book</i>	<i>Vol.</i>	<i>No.</i>	<i>Pages</i>	<i>Country</i>
Insurability (continued)							
Insurability of cyber risk: an empirical analysis	Christian Biener Martin Eling Jan-Hendrik Wirfs	2015	<i>The Geneva Papers on Risk and Insurance</i>	40	1	131–158	no specific
On the value of a checkup: adverse selection, moral hazard and the value of information	Neil Doherty Lisa Posey	1998	<i>The Journal of Risk and Insurance</i>	65	2	189–211	
Prädikative Gesundheitsinformationen bei Einstellungsuntersuchungen	unknown	2007	<i>Stellungnahme Nationaler Ethikrat Deutschland</i>				Germany
Reconciling privacy and speech in the era of big data: a comparative legal analysis	Ronald Krotosynski	2015	<i>William & Mary Law Review</i>	56	4	1279–1338	no specific
Reducing asymmetric information in insurance markets: cars with black boxes	Lilia Filipova-Neumann Peter Welzel	2010	<i>Telematics and Informatics</i>	27	4	394–403	no specific
Regulating genetic information in insurance markets	Michael Hoy Michael Ruse	2005	<i>Risk Management and Insurance Review</i>	8	2	211–237	no specific
What do we know about cyber risk and cyber risk insurance?	Martin Eling Werner Schnell	2016	<i>The Journal of Risk Finance</i>	17	5	474–491	no specific
Insurtech							
The current insurtechs landscape: business models and disruptive potential	Alexander Braun Florian Schreiber	2017	<i>I.VW-HSG Schriftenreihe</i>	62			no specific
101 insurtech startups revolutionizing the \$4.5-trillion-dollar insurance industry	Elena Mesropyan	2016	<i>Let's Talk Payments</i>				no specific
Fintech 100: leading global fintech innovators report 2015	unknown	2015	Industry study (KPMG and H2 Ventures)				no specific
Insurtech Übersicht DACH	Sascha Noack	2016	Industry study (New Players Network)				Germany, Switzerland, Austria
InsurTech(s): Zwischen Konkurrenz und Partnerschaft	Klaus Wiener Anja Theis	2017	GDV – Makro und Märkte	9			Germany
Insurtech: assembled for takeoff? The German insurtech universe and its disruptive potential	Christopher Schmitz Olaf Johannsen Danilo Raponi Bastian Hengstler	2016	Industry study (EY)				Germany
The pulse of fintech Q2 2016: global analysis of fintech venture funding	unknown	2016	Industry study (KPMG and CBInsights)				no specific
Zukunft von Insurtech in Deutschland. Der Insurtech-Radar	Dietmar Kottmann Nikolai Dödrchter	2016	Industry study (Oliver Wyman and Policen Direkt)				Germany

Table A. Dataset of papers and industry studies (continued)

<i>Title</i>	<i>Author(s)</i>	<i>Year</i>	<i>Journal/Book</i>	<i>Vol.</i>	<i>No.</i>	<i>Pages</i>	<i>Country</i>
Management survey							
Assekuranz 2015 - Eine Standortbestimmung. Neue Koordinaten im deutschsprachigen Versicherungsmarkt	Hato Schmeiser Angela Zeier Andrea Fürnthal Vania Bätig Benjamin Burr Cynthia Stampfli André Schlieker	2010	Industry study (I.VW-HSG and Accenture)				Germany, Switzerland, Austria
Die digitale Transformation in der Versicherungsbranche	Peter Roßbach Walter Kuhlmann Marc Laszlo	2015	Industry study (Q.Penior)				Germany, Switzerland, Austria
Digital maturity and transformation report	Sabine Berghaus Andrea Back Bramwell Kaltenrieder	2016	Industry study (I.WI-HSG and Crosswalk)				Germany, Switzerland
Digital transformation report 2015	Andrea Back Sabine Berghaus Bramwell Kaltenrieder	2015	Industry study (I.WI-HSG and Crosswalk)				Germany, Switzerland
Evolution of strategic levers in insurance claims management: an industry survey	Nils Mahlow Joël Wagner	2016	<i>Risk Management and Insurance Review</i>	19	2	197–223	Germany, Switzerland
Global digital insurance benchmarking report 2015	Florian Mueller Henrik Naujoks Harshveer Singh Gunther Schwarz Andrew Schwedel Kirsten Thomson	2015	Industry study (Bain & Company)				no specific
Industrialisierung der Assekuranz in einer digitalen Welt	Peter Maas Pascal Bühler	2015	Industry study (I.VW-HSG and Adecubum)				Germany, Switzerland, Austria
Insurance in a digital world: the time is now	unknown	2013	Industry study (EY)				no specific
Mit Daten Werte schaffen	unknown	2016	Industry study (KPMG and Bitkom)				Germany
Regulation							
Expanding innovation law, information technology and insurance	Alexander Traum	2016	<i>Journal of Internet Law</i>			July	no specific

Table A. Dataset of papers and industry studies (continued)

<i>Title</i>	<i>Author(s)</i>	<i>Year</i>	<i>Journal/Book</i>	<i>Vol.</i>	<i>No.</i>	<i>Pages</i>	<i>Country</i>
Strategic outlook							
Auf dem Weg zum Omni-Kanal	Gero Matouschek Bodo von Hülsen	2015	<i>Change Management in Versicherungsunternehmen: Die Zukunft der Assekuranz erfolgreich gestalten</i>			335–352	Germany, Switzerland, Austria
Digital distribution in insurance: a quiet revolution	Darren Pain Külli Tamm Ginger Turner	2014	Industry study (Swiss Re)				no specific
Digital reinvention: trust, transparency and technology in the insurance world of tomorrow	Christian Bieck Anthony Marshall Sandip Patel	2014	Industry study (IBM)				no specific
Digital transformation and insurance	Dr. Fabian Sommerrock	2016	Presentation during the 16th Asia CEO Insurance Summit				no specific
Digitalisierung: Der Schweizer Versicherungssektor im Umbruch	Pia Tischhauser Matthias Naumann Angelo Candreia Stephan Treier Julia Senger	2016	Industry study (The Boston Consulting Group & Google)				Switzerland
Digitization in life insurance: a prerequisite for success in spite of low interest rates	Daniel Berger Patrick Broer David Pankoke	2016	<i>I.VW-HSG Trendmonitor</i>	1		15–19	no specific
Dying, surviving or thriving. Strategic analysis of the future Swiss insurance market	Achim Bauer Yamin Gröninger Julius Scheidt Ricardo Garcia Edvin Rimpö	2016	Industry study (EY)				Switzerland
Insurance on the threshold of digitization: implications for the life and p&c workforce	Sylvain Johansson Ulrike Vogelgesang	2015	Industry study (McKinsey & Company)				no specific
Insurance technology strategy: time to re-evaluate	Ronald Pressman	2003	<i>The Geneva Papers on Risk and Insurance</i>	28	1	39–64	no specific
Leading a digital transformation in insurance	Harshveer Singh Gunther Schwarz Henrik Naujoks Andrew Schwedel	2014	Industry study (Bain & Company)				no specific
Life insurance in the digital age: fundamental transformation ahead	Jonathan Anchen Astrid Frey Milka Kirova	2015	Industry study (Swiss Re)				no specific

Table A. Dataset of papers and industry studies (continued)

<i>Title</i>	<i>Author(s)</i>	<i>Year</i>	<i>Journal/Book</i>	<i>Vol.</i>	<i>No.</i>	<i>Pages</i>	<i>Country</i>
Strategic outlook (continued)							
Raising your digital quotient	Tanguy Catlin Jay Scanlan Paul Willmott	2015	Industry study (McKinsey & Company)				no specific
Strategy, not technology, drives digital transformation – becoming a digitally mature enterprise	Gerald Kane Doug Palmer Anh Nguyen Phillips David Kiron Natasha Buckley	2015	<i>MIT Sloan Management Review</i>				no specific
Telematics strategy for automobile insurers	Johannes Paefgen Elgar Fleisch Lukas Ackermann Thorsten Staake Jonas Best Lukas Egli	2013	Whitepaper (I-LAB)				Austria, Germany, Switzerland
The Customer-centric insurer in the digital era	Andrea Moneta	2014	Industry study (Accenture)				no specific
The debate on the insurance value chain	Anton van Rossum Robert Mendelsohn Henri de Castries	2002	<i>The Geneva Papers on Risk and Insurance</i>	27	1	89– 101	no specific
The digitization of everything: how organizations must adapt to changing consumer behavior	Richard Ingleton Yunus Ozler Pippa Thomas	2011	Industry study (EY)				no specific
The hallmarks of digital leadership in p&c insurance	Tanguy Catlin Ido Segev Holger Wilms	2016	Industry study (McKinsey & Company)				U.S.
The impacts of digitization on the management of insurance companies: steering business in a digital world	Stefan Hrendlmeier Mark Hertting	2015	Industry study (Horvath & Partners)				no specific
The making of a digital insurer: the path to enhanced profitability, lower costs and stronger customer loyalty	Tanguy Catlin Rob Hartmann Ido Segev Ruxandra Tentis Frank Levy Richard Murmane	2015	Industry study (McKinsey & Company)				no specific
The new division of labor: how computers are creating the next job market		2005					no specific
Versicherungen: Die digitale Herausforderung	Gero Matouschek Henrik Naujoks Gunther Schwarz Bodo von Hülsen	2013	Industry study (Bain & Company)				Germany, Switzerland, Austria

Table A. Dataset of papers and industry studies (continued)

Technology	<i>Title</i>	<i>Author(s)</i>	<i>Year</i>	<i>Journal/Book</i>	<i>Vol.</i>	<i>No.</i>	<i>Pages</i>	<i>Country</i>
7 big data techniques that create business value		Debbie Stephenson	2013	Firmex				no specific
AI in insurance: hype or reality?		Unknown	2016	Industry study (PWC)				no specific
Analysis of fraud detection in insurance claim		Neelam Tak Shalini Rajawat	2016	<i>International Journal of Recent Trends in Engineering & Research</i>	2	7	136–140	no specific
Anything you can do, AI can do better: machine learning and artificial intelligence in insurance		Morag Cuddeford Jones	2016	White paper (Insurance Nexus)				no specific
Beyond the hype: big data concepts, methods, and analytics		Amir Gandomi Murtaza Haider	2015	<i>International Journal of Information Management</i>	35	2	137–144	no specific
Big data in the finance and insurance sectors		Kazim Hussain Elsa Prieto	2016	<i>New Horizons for a Data-Driven Economy</i>			209–223	no specific
Blockchain applications in insurance		Alexander Shelkovnikov	2016	Industry study (Deloitte)				U.K.
Blockchain in insurance – opportunity or threat?		Johannes-Tobias Lorenz et al.	2016	Industry study (McKinsey & Company)				no specific
Blockchain technology: beyond bitcoin		Michael Crosby Nachappan Pradan Pattanayak Sanjeev Verma Vignesh Kalyanaraman	2016	<i>Applied Innovation Review</i>	2			no specific
Bringing big data to life: four opportunities for insurers		Eric Brat Paul Clark Pranay Mehrotra Astrid Stange Céline Boyer-Chammard	2014	Industry study (The Boston Consulting Group)				no specific
Chatbot and the rise of the automated insurance agent		Rick Huckstep	2017	<i>The Digital Insurer</i>				no specific
Data mining – what it is and why it matters		unknown	2017	Industry study (SAS)				no specific
Ethereum dapps showcase: peer to peer insurance applications		unknown	2016	<i>Digital Insurance Observer</i>				
From data mining to knowledge discovery in databases		Usama Fayyad Gregory Piatetsky-Shapiro Padhraic Smyth	1996	<i>AI Magazine</i>	17	3	37–54	no specific

Table A. Dataset of papers and industry studies (continued)

<i>Title</i>	<i>Author(s)</i>	<i>Year</i>	<i>Journal/Book</i>	<i>Vol.</i>	<i>No.</i>	<i>Pages</i>	<i>Country</i>
Technology (continued)							
How insurers can invest in big data analytics to improve decision making	Henrik Naujoks Lori Sherer	2015	Industry study (Bain & Company)				
Insurance technology 2.0: an interactive process for 2013	Richard Weber	2013	<i>Journal of Financial Service Professionals</i>	March			no specific
Smart contracts in financial services: getting from hype to reality	Bart Cant Amol Khadikar Antal Ruiter Jakob Bolgen Bronebakk Jean Coumaros Jerome Buvat Abhishek Gupta Robert Puelz	2016	Industry study (Capgemini Consulting)				no specific
Technology's effect on property-casualty insurance operations	Robert Puelz	2010	<i>Risk Management and Insurance Review</i>	13	1	85–109	no specific
Telematics: connecting the dots	Andrea Keller Fabian Transchel	2016	Industry study (Swiss Re)				no specific
The drive to digitization in insurance. Turning “big paper” into big profit	Mark Breathing	2012	Industry study (SMA - Strategy Meets Action)				no specific
The evolution of analytics: opportunities and challenges for machine learning in business	Patrick Hall Wen Phan Katie Whitson	2016	Sebastopol, CA: O'Reilly Media and SAS				no specific
The sharing economy	unknown	2015	Industry study (PWC)				no specific
The sharing economy: your business model's friend or foe?	Wolfgang Kathan Kurt Matzler Viktoria Veider	2016	<i>Business Horizons</i>	59		663–672	no specific
Transforming into an analytics-driven insurance carrier	Ari Chester Richard Clarke Ari Libarickian	2016	Industry study (McKinsey & Company)				no specific
Trends in der Technologie sowie Erkenntnisse des Behavioural Pricings vereinbaren	Michael Hartmann Christoph Nützenadel	2015	<i>I.VW HSG Trendmonitor</i>		1	3–9	no specific
What “digital” really means?	Karel Dörner David Edelman	2015	Industry study (McKinsey & Company)				no specific
What is artificial intelligence?	John McCarthy	2007	AI questionnaire				no specific

Appendix B Definitions of digitalization

Table B. Definitions of digitalization

Source	Definition digitalization
Back et al. (2016) (translated from German)	“Digital transformation” is the combination of change in strategy, the business model, organization/processes and culture in companies by using digital technologies to enhance the competitiveness.
Catlin et al. (2015)	Six areas to succeed in a digital era: 1. <i>Digital analytics and decision making</i>: Data from both internal and external sources is gathered in real time and mined for actionable insights. 2. <i>Strategy</i>: A digital strategy adapts to rapid industry change while supporting overall business aspirations. 3. <i>Customer centricity</i>: Digital tools improve the customer experience at every step in the decision journey, and beyond. 4. <i>Digitize business processes</i>: Processes are reimagined from a zero base, reducing costs and errors, and boosting customer satisfaction. 5. <i>Organize for digital</i>: The corporate culture, approach to talent and organizational model all support digital excellence. 6. <i>Technology</i>: Two-speed IT allows for rapid digital development and ensures that transactional systems are safely maintained.
Dörner and Edelman (2015)	[...] we believe that digital should be seen less as a thing and more a way of doing things. To help make this definition more concrete, we’ve broken it down into three attributes: creating value at the new frontiers of the business world, creating value in the processes that execute a vision of customer experiences, and building foundational capabilities that support the entire structure.
Hiendlmeier and Hertting (2015)	In other words, it is only when the six components technology, data, processes/use cases, analytics, business impact and mobility come together that there is any meaningful contribution [...] it is more appropriate to use the term digitization as this brings together all the instruments and possibilities resulting from linking together technology, data, analytics and concrete business processes.
Ingleton et al. (2011)	Defining “digital.” Digitization at its simplest means the conversion of analogue information into digital information. As digitization capabilities extend, virtually every aspect of life is captured and stored in some digital form, and we move closer towards the networked interconnection of everyday objects. The impact of this is a real-time global exchange of information between multiple connected devices (fixed and mobile).
Müller et al. (2015)	Six dimensions of digital transformation: 1. <i>Digitally enhanced customer experience</i>: Insurers need to understand customers’ digital behaviors and priorities in order to design the appropriate offerings and experience. The leaders are reengineering moments of truth, such as lodging a claim, to integrate digital components. 2. <i>An omnichannel sales and distribution model</i>: Customers increasingly expect their insurers to have robust online and mobile channels, with technology integrated seamlessly into activities such as contact center conversations. 3. <i>Optimized operations using digital technologies</i>: Digital can play a big role in simplifying operations by trimming redundant and manual processes while speeding up turnaround times and reducing error rates. 4. <i>Advanced analytics and big data applied throughout the business</i>: Big data holds the potential for step change improvements in customer segmentation, risk calculation, fraud identification and other areas. But it takes time to develop an advanced analytics capability staffed by the right people and then to focus them on the highest-priority issues. 5. <i>Technology activated to enable a digital transformation</i>: The challenge is to cost-effectively enhance IT infrastructure and capabilities, either internally or through off-the-shelf systems. 6. <i>An innovation-ready organization</i>: Becoming a digital innovator requires creating an environment that fosters rather than stifles innovation, and encouraging active collaboration across functions and business units
Tischhauser et al. (2016) (translated from German)	Digitalization is the integration of new technologies with the aim of: 1. Industrialization and automation of business processes to enhance the efficiency, quality and throughput speed and to reduce costs at the same time 2. Transformation of the interaction between customer and insurer along the customer journey by adapting the frontend interfaces (e.g., mobile, apps, websites) to the changing customer requirements

Appendix C Value-chain and technology matrix

Table C. Value-chain and technology matrix – summary of technology impact

Value-chain process	Artificial intelligence	Big data	Internet of things	Blockchain	Cloud computing	Apps	Chatbots	Robo advisor	Website	Social network messenger internet forum	Video calls	Video platforms
Primary activities												
Marketing	---	More precise calculations	---	---	---	---	---	---	Advertisement and product information	---	---	Information platform
Product development	---		New products and prevention	New smart contracts	---	---	---	---	---	---	---	---
Sales	Sales without a human agent	Full picture of the customer through many data	---	---	New sales channel, partly fully automated	Sales without a human agent	---	---	Location-independent consultation and new acquisition channel	---	---	---
Underwriting	New possibilities for risk assessment	More precise calculations	Telematics data used for pricing	Automated underwriting	Digital document processing	---	---	---	---	---	---	---
Contract administration/customer service	Service without a human agent	---	Preventative support for clients	---	---	---	---	---	Location-independent customer service	---	---	---
Claim management	Fraud analysis and payout calculation	---	---	Automated payout	---	Claims are filed via App	---	---	---	---	---	---
Asset management	---	---	---	Decreasing transaction costs	---	---	---	Automated asset management	---	---	---	---
Risk management	Advanced risk analysis	---	---	---	---	---	---	---	---	---	---	---
Support activities												
General management	Analytical support in the decision process	---	---	---	Digital document processing	---	---	---	---	More efficient internal communication	---	---
IT	---	---	Automated trouble reports	---	---	---	---	---	---	---	---	---
Human resources	---	Employee analysis	---	---	Digital document processing	---	---	---	Recruitment channels, usage of video calls for training of employees	---	---	---
Controlling	Automated auditing of contracts and data	---	---	---	---	---	---	---	---	---	---	---
Legal department	---	---	---	---	---	---	---	---	---	---	---	---
Public relations	---	---	---	---	---	---	---	---	---	---	---	New communication channels

Essay II: Balancing the desire for privacy against the desire to hedge risk

Abstract

An individual's desire to hedge risks, as implied by risk aversion, is accepted as a normative paradigm and documented as valid descriptively. Insurance markets satisfy this desire, wherein the individual's aversion to bear risk allows firms to demand a markup on the expected value of the insured loss. Insurance firms incrementally introduce digital monitoring technology into their policies, making policyholder's behavior transparent. We analyze the implications of such transparency insurance contracts for willingness to pay in a framed behavioral experiment and find that the loss of privacy in such contracts marginalizes the potential profits that insurers could earn on their policies. In particular, our results suggest that the reduction in willingness to pay from introducing digital monitoring is in the range of 25 to 50 percent of the expected loss. While an absolute as opposed to a relative monetary valuation concept of privacy appears more likely to explain our data, we cannot clearly confirm this conjecture empirically. Heterogeneous treatment effects for risk preferences are suggestive for increasing utility losses from transparency policies with increasing risk aversion but we also observe indications of nonlinearities in this relationship. Probability misperception is a salient characteristic of our experimental population, suggesting that profitability is less threatened under low-frequency risks as opposed to high-frequency risks.

Keywords

Information privacy preferences, risk preferences, digital monitoring; insurance

Christian Biener, Martin Eling, Martin Lehmann (2020).

This paper was presented at the 5th and 6th research seminar of the Institute of Insurance Economics at the University of St. Gallen, the 2017 Frankfurt Insurance Research Workshop of International Center for Insurance Regulation (ICIR) at Goethe University Frankfurt, the 2018 Ph.D. in Finance Seminar at the University of St. Gallen, the 2018 annual meeting of the German Insurance Science Association in Munich, the 2018 annual meeting of the American Risk and Insurance Association (ARIA) in Chicago, and the 2018 CEAR/MRIC Behavioral Insurance Workshop in Munich.

This paper has been accepted for publication in the *Journal of Economic Behavior and Organization*.

1 Introduction

Insurance allows agents to transfer their exposure to economic losses to a principal in exchange for an ex-ante premium. For this risk transfer to be efficient, hidden information issues with regard to individuals' risk type in addition to the potential behavioral changes that give rise to hidden action must be properly addressed. The typical schemes to reduce the negative welfare effects of such information asymmetries are well documented in the literature and include some form of screening and signaling to address hidden information problems (Rothschild & Stiglitz, 1976; Crocker & Snow, 2011; Hoy, 1982; Browne & Kamiya, 2012; Hoy & Ruse, 2005) and partial risk-sharing through deductibles and coinsurance to address hidden action (Pauly, 1968; Holmström, 1979).

With the rise of new technology, insurers have the tools to mitigate information asymmetries by conditioning insurance contracts on observed behavior and thus on risk type directly through the use of digital monitoring devices. We refer to such contracts as *transparency contracts*.³⁶ Given that technology costs are low (or even zero) and that observed behavior is indeed a good signal of risk type, transparency contracts naturally appear to increase efficiency because they eliminate information asymmetries, allowing for the reduction of partial risk-sharing and thus improved welfare.³⁷ The resolution of hidden information and hidden action, however, comes at a cost to individuals seeking more coverage—the disutility of giving up privacy (Gemmo, Browne, & Gründl, 2019)—implying a willingness to pay (WTP) for privacy.

In this study, we quantify the disutility of giving up privacy by measuring the differential WTP for transparency and standard full insurance contracts in an incentivized framed laboratory experiment. While a large stream of literature analyzes the economic value of privacy protection and disclosure,³⁸ it is empirically unclear, how the disutility of giving up privacy is evaluated in the context of risk and insurance. A fundamental methodological problem this study addresses is the incentive-compatibility and saliency

³⁶ Transparency contracts are widely used in motor insurance (e.g., Progressive, Allstate, Metromile, Generali) and health insurance (e.g., Generali); see Eling and Kraft (2017).

³⁷ While under hidden information the insurer can offer full insurance to high risk types but only partial insurance to low risk types at fair rates (Rothschild & Stiglitz, 1976), full coverage contracts for both types are feasible and efficient at fair rates in the absence of informational asymmetries. Similarly, partial risk-sharing can be reduced if premiums can condition on observed behavior solving moral hazard.

³⁸ For example, Cvrcek, Kumpost, Matyas, and Danezis (2006) analyze the participation fee for an artificial mobile network study. Jentzsch, Preibusch, and Harasser (2012) find that people provide more private information for a less expensive cinema ticket. Hui, Teo, and Lee (2007) find that monetary incentive and a privacy statement induces subjects to share more private information. Feri, Giannetti, and Jentzsch (2016) analyze the impact of data-breach notification and Schudy and Utikal (2017) measure the willingness to share personal data with anonymous recipients.

of privacy losses that is absent in most of the extant research. To assure saliency of privacy losses, participants must disclose their personal data if they opt into the transparency contract. In particular, participants commit to share location data for 1 or 8 hours via the mobile application WhatsApp with us. We follow the arguments by Benndorf and Normann (2018) that privacy experiments should be incentivized, salient, and transparent. Especially, we think that a lack of salience of privacy invasion could lead to experimenters being unable to identify treatment effects.³⁹ We also investigate the role of risk, privacy preferences, personal characteristics, and personality in explaining the WTP for privacy.

Our results show that the loss of privacy in transparency contracts substantially reduces the potential profit an insurer might earn. In particular, we find that the reduction in WTP from introducing digital monitoring is in the range of 25 to 50 percent of the expected loss. While we document increasing utility losses (i.e., treatment effects) from transparency policies with increasing risk aversion we also find indications of nonlinearities in this relationship. Probability misperception is salient in our experimental population. Individuals overweight small probabilities making them more averse to low-frequency risks. In our context, this implies that profitability is threatened more for insurance policies covering high frequency risks as opposed to low-frequency risks because the overweighting of small probabilities increases WTP relative to the economic value of the policy more for low-frequency risks. With regard to other observed personal characteristics such as gender and Big Five personality traits, treatment effects are homogeneous. We also do not find a significant link between a set of survey measures for privacy preferences and our observed treatment effects. This indicates a potential mismatch between incentivized and non-incentivized data that is commonly found in the literature (Baillon, 2017; Benndorf & Normann, 2018).

We contribute to the empirical literature on the valuation of privacy in general and, to the best of our knowledge, provide the first incentive-compatible quantification of utility losses from monitoring in the field of insurance. Furthermore, our analysis contributes to the discussion of welfare implications of digital monitoring in insurance and related economic fields. In this context, digital monitoring has the potential to resolve market failure as it mitigates information asymmetries. As we argue in this paper, welfare from proper functioning of the market for risk transfer needs to be balanced against welfare

³⁹ For example, Beresford, Kübler, and Preibusch (2012) analyze DVD purchases from two stores that demand different kinds of private data (income/date of birth versus favorite color/year of birth). When DVD prices are the same, they find no significant difference in DVD purchases per store. Although, participants indicate strong privacy preferences. They conclude that people are unwilling to pay for privacy and revealed privacy preferences are not in line with actual behavior. Another possible explanation could be that asking students for income and their date of birth might not be salient enough as their income might be comparable and they may find age information not sensitive enough.

from individual privacy. Our research could help understand if mandatory data sharing with insurance companies—for example, a legal requirement for telematic devices in auto insurance—is welfare-increasing. At the level of insurance firms, our results help to judge demand-side costs of such contracts in terms of changes in WTP.

The remainder of this paper proceeds as follows. In Section 2, we introduce the theoretical framework. In Section 3, we explain the experimental design. Section 4 includes the experimental results and we conclude in Section 5.

2 The value of personal data

In this section we define the individual value of private data and shared private data. We conjecture that every individual can be described by a finite set of n data points and that I be the set of all possible data points (e.g., name, age, gender, date of birth, phone number, geographical location). Now, consider an individual j , which can be described by I .⁴⁰ We define $x^j = (x_{data\ 1}^j, \dots, x_i^j, \dots, x_{data\ n}^j)$, with $i \in I$, as the vector indicating if an individual j has a particular data point i ($x_i^j = 1$) or not ($x_i^j = 0$). Additionally, we define $v_i^j \in (0, \infty)$ as the monetary value individual j assigns to each of her data points $i \in I$. For brevity we neglect superscript j and define the value of private data (VoD) as the sum of the value of each data point:

$$(1) \quad VoD = v_{data\ 1}x_{data\ 1} + \dots + v_{data\ n}x_{data\ n} = \sum_{k=1}^n v_{data\ k}x_{data\ k}.$$

Moreover, if $s = (s_{data\ 1}, \dots, s_i, \dots, s_{data\ n})$, with $i \in I$, is the vector indicating which data points have to be shared ($s_i = 1$) in a contractual relationship such as an insurance contract,⁴¹ we can define the value of shared data ($VosD$) as:

$$(2) \quad VosD = s_{data\ 1}v_{data\ 1}x_{data\ 1} + \dots + s_{data\ n}v_{data\ n}x_{data\ n} = \sum_{k=1}^n s_{data\ k}v_{data\ k}x_{data\ k}.$$

The definition of $VosD$ is broad and applicable to a variety of contexts. In our (insurance) setting, consider an agent with von Neumann-Morgenstern utility $U(\cdot)$, with $U'(\cdot) > 0$ and initial wealth w_o , who is subject to a random loss $D < w_o$ with probability π . Agents can buy a full-coverage insurance policy for premium P .

⁴⁰ While some datapoints are present in all individuals and mostly exogenous (e.g., age, gender), the existence of some datapoints such as owning particular items is endogenous.

⁴¹ The data that has to be shared depends on the situation and on the purpose of data sharing. Also, with our notation, we assume that the assigned value to each data point is equal in every situation, which is a rather simplified assumption. Moreover, we assume that VoD and $VosD$ can be decomposed in additive values of each datapoint and that the values are independent from each other. Acquisti, Taylor, and Wagman (2016) describe privacy preferences as dynamic, subjective and context dependent. For example, Schudy and Utikal (2017) show that the willingness to share data decreases with the number of recipients. This could be included in our formula by letting v_i depend on the situation.

The utility from the full-coverage insurance contract V_{FI} is given by:

$$(3) \quad V_{FI} = U(w_0 - P),$$

and the willingness to pay WTP_{FI} is defined as the premium for which the utility is equal to the expected utility of no insurance, thus:

$$(4) \quad U(w_0 - WTP_{FI}) = (1 - \pi)U(w_0) + \pi U(w_0 - D).$$

From Gemmo et al. (2019) we know that the utility of the transparency contract should include the disutility of giving up privacy ψ and thus can be defined as:

$$(5) \quad V_{Trans} = U(w_0 - P) - \psi.$$

With our definition of $VosD$ as a monetary value, we can include it in our utility function. This has some tractability benefits, rendering the model in line with traditional insurance demand models, and gives the value of shared data a natural interpretation. We thus obtain:

$$(6) \quad V_{Trans} = U(w_0 - P - VosD).$$

Equivalently to the indifference condition (4), the willingness to pay WTP_{Trans} for the transparency contract satisfies the following condition:

$$(7) \quad U(w_0 - WTP_{Trans} - VosD) = (1 - \pi)U(w_0) + \pi U(w_0 - D).$$

If individuals dislike giving up privacy and thus $VosD > 0$ and because $U(x)$ is increasing in wealth, it follows from (4) and (7) that $VosD = \Delta WTP = WTP_{FI} - WTP_{Trans} > 0$. Our expectation that $VosD > 0$ rests on the assumption that agents assign a positive value to their personal data. The limited literature appears to conclude that personal data has a positive value and that agents demand a premium to share such data (Tsai, Egelman, Cranor, & Acquisti, 2011; Feri et al., 2016; Benndorf & Normann, 2018). Also, benefits compensating for giving up privacy may be in forms other than monetary units such as additional benefits inherent in tailor made offerings (Acquisti et al., 2016). In addition to assigning a positive value to personal data, agents may be concerned that this data is vulnerable to inappropriate usage or access (Smith, Milberg, & Burke, 1996; Dinev & Hart, 2006). Accordingly, we formulate the following hypothesis:

Hypothesis 1: *Individuals experience a disutility from giving up privacy and thus $VosD = \Delta WTP > 0$.*

In our setting of dynamic location data, the intensity of the loss of privacy in terms of the duration of data sharing significantly determines the size of $VosD$, thus increasing the value of shared data. We are agnostic with regard to the exact functional relationship between the number of shared datapoints and the value of the sum of the shared data, which could be linear or nonlinear. In an incentivized experiment Schudy and

Utikal (2017) find that willingness to share data decreases with the number of people receiving the data, which could also be a measure for the shared amount of data. Benndorf and Normann (2018) also analyze utility losses when the amount of data increases but with inconclusive evidence.⁴² We have no prior expectation other than the following:

Hypothesis 2: *VosD increases with the duration of data sharing, i.e., $VosD' > 0$.*

Aside from hypothesizing $VosD > 0$ and $VosD' > 0$, we want to understand what a relevant reference point for assigning monetary values to privacy is. As individuals may have no benchmark concept as to the monetary value of the privacy discount $VosD$, they may be looking for cues in product characteristics, which are salient in the decision-making process. There are two of such salient characteristics, namely, the duration of data sharing and the expected value of the insurance πD . The first reference point implies a privacy discount $VosD$ that is not relative to the economic value of the insurance policy, while the latter reference point suggests the privacy discount $VosD$ to be relative to the economic value of the insurance policy. Identifying dependence characteristics helps us understanding under which conditions the disutility from privacy generates sustainability issues. If individuals apply a reference point concept that is independent of the probability information, it is easy to show that policies for low (as opposed to high) frequency risks that rely on shared private data are less likely to realize $WTP > \pi D$. Following our theoretical conjecture suggesting that $VosD$ is an absolute concept and the notion of privacy as a final good that represents preferences (Acquisti et al., 2016), we formulate the following hypothesis:

Hypothesis 3: *VosD is independent of the economic value of the insurance policy.*

Additionally, we control for the several dimensions of heterogeneity such as socio-demographics, personality, and participants' risk and privacy preferences, using established incentivized and non-incentivized survey measures.

3 Experimental design

In our behavioral experiment, we aim at identifying $VosD$. Our experimental task allows for an identification of threshold values in terms of WTP for which participants are willing to give up privacy. Prior to the experimental task, we gathered sociodemographic data and elicited an incentivized measure of risk preference. Survey measures of information privacy preferences along with personality characteristics were collected subsequent to the experimental task.

⁴² While their 89-participants within-subject results suggest lower willingness to sell for a combination of contact data and a set of preferences as opposed to the single components itself, between-subject estimates show no evidence of such differences.

3.1 Insurance game

We conducted a laboratory experiment in which subjects decide whether or not to purchase insurance in a risky environment. Participants received an initial endowment $w_o = 17 \text{ EUR}$, whereas $D = 15 \text{ EUR}$ are exposed to a loss with probability $\pi \in \{0.2, 0.3\}$. In each of 15 binary decisions with varying insurance premiums P between 0.50 EUR and 7.50 EUR (in 0.50 EUR increments), participants can opt to purchase a full insurance contract.⁴³ This design is incentive-compatible (Cummings, Harrison, & Rutström, 1995) and incorporates the prospect of losing instead of winning money as stressed, for example, by Harrison and Rutström (2008). The payoff of participants thus is $w_o - P$ if insurance is purchased or $w_o - D$ with π and w_o with $1 - \pi$ if insurance is not purchased. Participants in the different experimental conditions face the same decisions. In some of the treatment conditions, however, we included the obligation to share live location data with us if insurance was purchased.

After participants made their choices, one choice was randomly drawn and the respective insurance game was played out. If they choose the full insurance or transparency contract, they have to pay the premium from their initial endowment and, in case of the transparency contract, share their live location data. Subsequently, if they have not chosen the full insurance contract, we play out the risk with probability $\pi \in \{0.2, 0.3\}$. The outcome of the game determines the actual payout of the participants.

3.2 Treatments

Every participant played all five of the experimental conditions presented in Table 6 and was randomly assigned to one of 24 unique orders of these conditions, ensuring that an equal number of participants was allocated to each of the five conditions being played first in order.⁴⁴ Thus, our experimental design theoretically allows for a clean between-subject analysis (i.e., only using the decisions from the condition played first) and a within-subject analysis. Because of order effects, we rely on the between-subject analysis in the empirical analysis throughout the paper. The insurance treatments were divided into two primary treatments: low-risk treatments with a loss probability of 20 percent and high-risk treatments with a loss probability of 30 percent. Both primary

⁴³ In a multiple price list design, we asked participant for each of 15 premium amounts ranging from 0.50 EUR to 7.50 EUR if they would like to purchase the insurance contract. We did not randomize the order, so participants saw the complete list at once on a computer screen, making it easier to comprehend the task. The highest premium a participant would pay for the insurance contract determines our willingness to pay for this participant in a particular treatment.

⁴⁴ Treatment orders are based on the two blocks with either 20 or 30 percent loss probability. We blocked these conditions to avoid confusion of participants through alternating loss probabilities. Within these blocks, we used all possible permutations (i.e., 6 and 2) and then either played the 20 or the 30 percent block first, resulting in 24 unique treatment orders.

treatments again included sub-manipulations varying the duration of location data sharing (i.e., 1 or 8 hours). While the rationale for varying the duration of location data sharing was to vary the severity of the privacy manipulation (see hypothesis 2), the rationale to vary loss probability is to see, whether people evaluate privacy relative to the economic value of the insurance policy, or in absolute terms (see hypothesis 3).

Table 6. Experimental treatment conditions

Panel A: Universal parameters					
Initial endowment	17 EUR				
Loss	15 EUR				
Insurance coverage	15 EUR				
Panel B: Treatment characteristics					
	Low risk			High risk	
	C ₂₀	T _{20-1h}	T _{20-8h}	C ₃₀	T _{30-8h}
Loss probability	0.2	0.2	0.2	0.3	0.3
Duration of location data sharing	0	1	8	0	8
	hours	hour	hours	hours	hours
Expected value of full-coverage insurance	3.00	3.00	3.00	4.50	4.50
Panel C: Participants and sessions					
Number of participants	96	98	99	96	96

Our experiment has $1 - \beta = 0.80$ power to precisely detect average treatment effects as small as 0.79 EUR in WTP or 18 percent of the expected value of the insurance policy under the high-risk conditions to 26 percent of the expected value of the insurance policy under the low-risk conditions at $\alpha = 0.05$. Type II error rates β are higher than 0.20 for smaller average treatment effects, meaning that we would fail to detect smaller treatment effects.

3.3 Preference measures and personality characteristics

We use the canonical Holt and Laury (2002) lottery choices with an extended set of explanations as in the Texas version of Charness, Eckel, Gneezy, and Kajackaite (2018) and Harrison, Johnson, McInnes, and Rutström (2005) to reduce noise and choice of dominant options.⁴⁵ We also add three sets of scaled Holt and Laury (2002) lotteries (see Harrison, Lau, & Rutström., 2007) to generate a better characterization of individual risk attitudes. Based on a total of 40 decisions, we estimate individual-level constant relative risk aversion (CRRA) (i.e., $U(Y) = \frac{Y^{(1-\rho)}}{(1-\rho)}$ for $Y > 0$) preference parameters, using standard maximum likelihood specifications of random utility models (RUM) such as introduced in Hey and Orme (1994), Holt and Laury (2002), Harrison and Rutström (2008), or Harrison and Ng (2016) as well as a random parameter model (RPM) recently introduced in Apesteguia and Ballester (2018). We use the alternative RPM

⁴⁵ There are several methods to measure risk preferences in an experiment, e.g., questionnaires (e.g., Dohmen et al., 2011), investment decision (e.g., Gneezy & Potters, 1997), gambling choices (e.g., Eckel & Grossman, 2002) and multiple price list (Holt & Laury, 2002). For a comprehensive review of experimental methods to elicit risk preferences, see Charness, Gneezy, and Imas (2013).

specification because of recent criticism of non-monotonicity of RUMs (Apestegua & Ballester, 2018). We use the Fechner error specifications popularized by Hey and Orme (1994) for the RUM, placing the error at the stage when expected utilities of lotteries are compared. In contrast to RUMs, the random error distorts the agent's preference parameter in RPMs (Apestegua & Ballester, 2018). Aside from the standard expected utility framework, we also fit a rank-dependent utility (RDU) model based on the one-parameter weighting function $w(p) = e^{(-(-LN(p))^{\gamma})}$ popularized by Prelec (1998).

To shed some light on the validity of frequently used survey measures to elicit privacy attitudes,⁴⁶ we include the “concern for information privacy” (CFIP) instrument by Smith et al. (1996), the most influential way to measure information privacy concerns (Preibusch, 2013).⁴⁷ For further potential determinants of our experimental measure of privacy attitudes (*VosD*), we include the Big Five personality inventory as the most popular instrument to measure personality traits.⁴⁸

3.4 Procedures and sample characteristics

We conducted the experiments in the experimental laboratory MaXLab of the University of Magdeburg using the web-based software QuestBack in June 2018. Experimental conditions were randomized at the individual level within each session. Participants were recruited through the student subject pool of the experimental laboratory and participants were required to have a good command of the German language.

The structure of an experimental session was as follows. First, a pre-experimental survey was conducted to gather participants' sociodemographic characteristics, followed by the lottery choice task to measure risk preference. Each participant then played all five of the experimental conditions while the order was conditional on random assignment. Detailed explanations were provided before the experimental decisions. Only one decision of one experimental condition was paid out at random. We explained the approximate duration, number of games, and payout mechanism to all participants in

⁴⁶ See Benndorf and Normann (2018) for a discussion of inconclusive evidence from non-incentivized privacy survey measures and their incompatibility with market values for personal data suggesting high levels of hypothetical bias (Harrison & Rutström, 2008).

⁴⁷ Because we conducted the experiment in German, we used the validated German translation of the CFIP by Harborth and Pape (2018).

⁴⁸ The instrument measures the personality in five dimensions: (1) openness; (2) conscientiousness; (3) extraversion; (4) agreeableness; (5) neuroticism, with 5-10 short items each. We rely on the 10-item short version to elicit Big Five personality traits as introduced in Rammstedt and John (2007).

advance. After the experiment, we administered a post-questionnaire to assess participants' privacy preference, personality, and numeracy.⁴⁹

The individual payout procedure, which was administered only after all tasks of the experimental session were completed, was as follows. Starting with the risk preference elicitation lotteries, one of the 40 decisions was chosen randomly by throwing a 6-sided die once to determine one of the four lottery lists and a 10-sided die to determine the lottery choice.⁵⁰ The outcome of a subsequent roll of the 10-sided die determined their payout. For the insurance game, we chose a similar procedure. First, participants determined one of the five insurance games played (by throwing a 6-sided die). Second, with a 20-sided die we determined the premium decision (0.50 EUR to 7.50 EUR) considered for payout.⁵¹ If participants did not buy the insurance in the selected decision, we rolled a 10-sided die to determine their payout.⁵² In contrast, if participants bought the insurance in the selected decision, the premium was deducted from their initial endowment and if the insurance contract required location data sharing, participants were obliged to share location data for 1 or 8 hours with us. For data sharing and tracking, we used the built-in GPS live data sharing in WhatsApp, where the time horizon of location data sharing can be set to 1 or 8 hours. To ensure the participants' compliance, we tracked their status on a regular basis, as communicated in the instructions (see Appendix B).⁵³ All of the final payouts were made the day after the experiment.

The laboratory currency was exchangeable to real EUR at a rate of 1:1. In addition to proceeds from the insurance game, participants received a participation fee of 4 EUR and proceeds from a lottery game to elicit risk preferences. The average earnings from the experiment were 20.5 EUR in total including proceeds from the insurance game of approximately 14 EUR, from the lottery choice task of approximately 2.5 EUR, and from the participation fee of 4 EUR.

In total, we conducted 35 sessions with 485 participants. Table 7 presents the mean values of individual characteristics and equality of means tests by treatment group. The

⁴⁹ To avoid any systematic effects of choice fatigue, we randomized the order of the individual tasks and made sure, the experimental session in its entirety is not too long (i.e., around 40 minutes including payment). Furthermore, we only use the decisions from the experimental condition that was played first by the participant (i.e., between-subject design).

⁵⁰ Participants throw the 6-sided die as long as a number between 1 to 4 appears to determine the lottery list.

⁵¹ Participants throw the 6-sided die as long as a number between 1 to 5 appears to determine the insurance game. The 20-sided die is thrown as long as a number between 1 to 15 appears, which determines the insurance premium.

⁵² In the low- (high-) risk condition, participants did lose 15 EUR if the die was 1 or 2 (1, 2 or 3) or kept the endowment of 17 EUR for all other numbers rolled.

⁵³ No location data was stored. We deleted all contact information of participants after the period of monitoring agreed with participants to comply with data protection laws.

results show that individual characteristics are balanced throughout the treatments (i.e., versus the control condition) and that only few variables exhibit significant differences.

Table 7. Summary statistics and balancing checks

<i>Variable</i>	<i>C₂₀</i>	<i>T_{20-1h}</i>	<i>T_{20-8h}</i>	<i>C₃₀</i>	<i>T_{30-8h}</i>	
	Mean ^a (Standard deviation)					Equality of means (p-value) ^b
Panel A: Sociodemographic characteristics						
Sex (1=female, 0=male)	0.479 (0.502)	0.469 (0.502)	0.455 (0.500)	0.458 (0.501)	0.469 (0.502)	0.998
Age (in years)	23.844 (3.226)	23.898 (3.501)	23.980 (3.511)	24.292 (3.264)	24.094 (3.476)	0.901
Relationship status (1=no single, 0=single)	0.458 (0.501)	0.439 (0.499)	0.384 (0.489)	0.438 (0.499)	0.427 (0.497)	0.875
Monthly income category ^c	1.448 (0.752)	1.429 (0.825)	1.394 (0.531)	1.354 (0.781)	1.323 (0.624)	0.730
Numeracy performance ^d	0.741 (0.168)	0.755 (0.177)	0.747 (0.177)	0.732 (0.196)	0.760 (0.162)	0.810
Panel B: Preference measures						
RUM CRRA coefficient	0.717 (0.367)	0.725 (0.359)	0.665 (0.317)	0.701 (0.564)	0.659 (0.312)	0.756
RPM CRRA coefficient	0.700 (0.735)	0.661 (0.351)	0.576 (0.333)	0.545 (0.387)	0.593 (0.357)	0.198
Risk preference survey measure ^e	5.240 (1.961)	4.745* (2.012)	5.020 (2.114)	5.042 (1.989)	5.000 (2.103)	0.574
Privacy preference ^f	5.617 (0.812)	5.566 (0.756)	5.558 (0.725)	5.596 (0.787)	5.426* (0.710)	0.448
Equality of means (<i>p</i> -value) ^b		0.798	0.781	0.391	0.452	0.862
Number of participants	96	98	99	96	96	

Notes: ^a Asterisks indicate the significance levels of the differences in means relative to the control group *C₂₀* based on clustered standard errors. ^b We report p-values for multivariate equality in means tests based on Wilks's lambda test statistics. Whereas the column p-values provide test results for equality of means of one variable across all treatments, the row p-values indicate test results for equality of means of all variables between the respective treatment and the control group. ^c Income categories are as follows: 1: ≤500 EUR, 2: >500 EUR to ≤1,000 EUR, 3: >1,000 EUR to ≤1,500 EUR, 4: >1,500 EUR. ^d Proportion of correct answers based on eight numeracy questions introduced by Weller et al. (2013). ^e Scores are based on a ten-point Likert scale questionnaire item, where 0 indicates "not at all willing to take risks" and 10 means: "very willing to take risks." ^f Scores are based on seven-point Likert scale questionnaire items, where 7 indicates strong accordance, i.e., a score of 7(1) indicates high (low) concerns about privacy.

*** Significant at the 1 percent level.

** Significant at the 5 percent level.

* Significant at the 10 percent level.

4 Experimental results

4.1 Main results

This section presents the main hypotheses tests as well as an analysis of heterogeneous treatment effects. Because of the censored nature of our dependent variable,⁵⁴ simple ordinary least squares regressions would provide inconsistent estimates of the treatment effects, meaning that these would not necessarily approach the true population parameters as sample size increases. We rely on the Tobit model to account for the censored nature of the data. All effect sizes and p -values shown in the subsequent discussion of the hypotheses are estimated from the respective Tobit regression models and can be reproduced from Table A in Appendix A. For reasons of clarity and comprehensibility, we rely on the visual representation of treatment effects in Figure 3 for most of the discussion, from which size and significance of the effects can be equally judged. We rely on the between-subject dimension of our data in the empirical analysis throughout the paper.

Hypotheses 1 and 2. Our first hypothesis states that the disutility from giving up privacy implies a reduction in WTP, i.e., $\Delta WTP > 0$, while the size of ΔWTP is expected to depend on the duration of data sharing in our second hypothesis. Our treatment effects provide strong support for both hypotheses. Under the low risk conditions, the impact of sharing live location data for 1 hour in T_{20-1h} is -25.4 percentage points (p -value = 0.076) in units of expected value from the insurance policy, while the impact of 8 hours of live location data sharing in T_{20-8h} is -49.6 percentage points (p -value = 0.001). Under the high-risk conditions, the impact of sharing live location data for 8 hours in T_{30-8h} is -26.3 percentage points (p -value = 0.017) in units of expected value from the insurance policy.

The treatment effects are economically relevant considering that the potential profit margins that can be generated from insurance policies are cut down from 63.5 percentage points to 13.9 percentage points under the low-risk condition when introducing a monitoring scheme. Under the high-risk condition, it is striking that individuals are barely willing to pay the expected value of the insurance policy.

⁵⁴ The dependent variable (i.e., ratio of willingness to pay to the expected value of the policy) is censored from below at 0 as well as censored from above at 2.50 for the low-risk conditions and at 1.67 for the high-risk conditions. The censoring comes from the fact that the maximum WTP for which participants could choose between buying or not buying was 7.50 EUR. This is then set in relation to the expected loss of either 3 EUR (i.e., under the low-risk condition) or 4.50 EUR (i.e., under the high-risk condition). A concern could potentially be that censoring is more pronounced under the high-risk condition because of the lower distance of the expected loss to the maximum WTP. However, this is not the case with 17.1 percent of observations censored from above under the low-risk condition and 18.2 percent of observations censored from above under the high-risk condition.

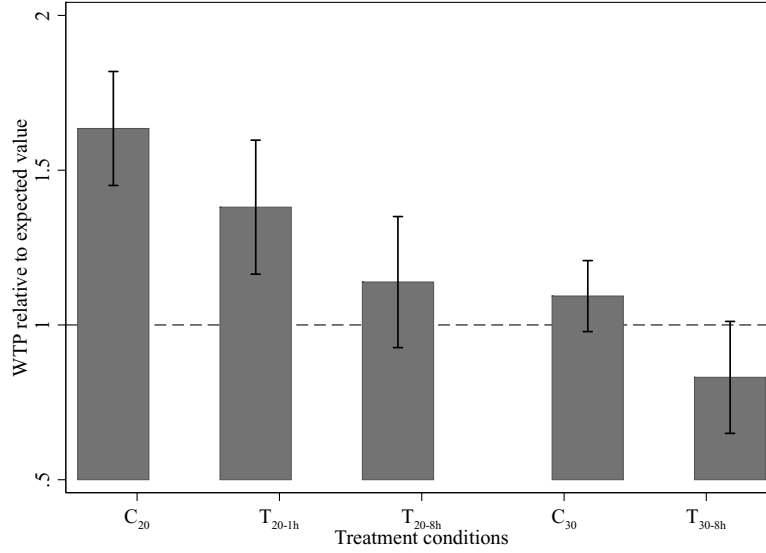


Figure 3. Mean WTP relative to expected value of insurance policy.

Notes: The bars represent the mean WTP relative to the expected value of the respective insurance policy of individuals for the different treatment groups estimated from Tobit regressions accounting for the censored nature of the data. Error bars indicate 95 percent confidence intervals based on clustered standard errors at the individual level.

In particular, they are willing to pay only 9.3 percentage points more on average, which is not statistically different from 0 (p -value = 0.110). Introducing the data-sharing scheme into this setting reduces the WTP to below the expected value of the insurance policy (i.e., 83.1 percent of the expected value). To put this into perspective, actual market estimates for markups on the expected loss are in the range of > 20 percent.⁵⁵ The difference in relative WTP between the low-risk and the high-risk condition is puzzling. There is a 54.2 percentage point difference (i.e., 63.5 percentage points versus 9.3 percentage points) that cannot be explained by standard expected utility models.⁵⁶ An obvious candidate to explain this difference is probability weighting reflected in RDU,

⁵⁵ Lower bounds for these markups can be estimated based on market data for expense and loss ratios. Assume L to be the losses incurred, E the expenses (e.g., employee wages, administrative costs, commissions for sales staff), and P the premium income of a particular insurer in a respective year. The expense $ER = \frac{E}{P}$ and loss ratios $LR = \frac{L}{P}$ are observable on the market. Given expense and loss ratios and assuming that $E(L) = L$ we can estimate relative markup on the expected loss as $\frac{E}{E(L)} = \frac{ER}{LR}$. Motor insurance in Europe, as an example, had expense ratios of 20 percent in 2012 and 2013 on average, while loss ratios were 79 percent (Insurance Europe, 2015), resulting in an average markup on the expected loss of 25 percent in these years. Using a different approach, Cummins et al. (2006) estimated economic premium ratios (EPRs), which have a similar interpretation, for property insurance in the US for 1997 to 2004, which are between 18 and 26 percent (i.e., the 95 percent confidence interval, which can be approximated from Table 5 in their study). However, the EPRs exclude underwriting expenses, which makes these estimates a lower bound for total markups on the expected loss.

⁵⁶ The willingness to pay a 63.5 percent markup under the low-risk condition implies a CRRA coefficient of $\rho = 0.73$. Given this level of risk aversion, that same individual should be willing to pay a 53.8 percent markup under the high-risk condition.

that is able to deal with the empirically observed probability dependence of risk tolerance. A plethora of research has shown that individuals do not treat probabilities at face value, but frequently overweight small and underweight high probabilities (Kahneman & Tversky, 1979; Quiggin, 1982; Prelec, 1998). To test this conjecture, we estimate population-level RDU model parameters for CRRA and probability weighting based on the one-factor probability weighting functional $w(p) = e^{(-(-\ln(p))^\gamma)}$ introduced in Prelec (1998). The results show significant probability weighting with $\gamma = 0.71$ on average.⁵⁷ The implied probabilities from probability weighting in our binary setting are $1 - w(0.8) = 29.2$ percent for the-low risk setting with objective loss probability of 20 percent and $1 - w(0.7) = 38.2$ percent for the high-risk setting with objective loss probability of 30 percent, leading to subjective expected losses of 4.37 EUR and 5.72 EUR respectively. Thus, WTP relative to the perceived expected value of the insurance is actually much more comparable between C_{20} and C_{30} with an average difference of only 26.2 percentage points. Half of the difference between WTP relative to the expected value of the insurance we observed in Figure 3 thus seems to be driven by probability weighting.

Altogether, our results suggest that the economically and statistically significant costs of introducing monitoring devices into an insurance setting need to be considered in conjunction with the generated benefits (e.g., risk selection, behavioral change). Our results are also relevant to welfare analyses considering that transparency contracts are becoming more important in actual markets. At some point it might be argued for mandatory monitoring⁵⁸ based on insurability arguments, for example, in situations of potential market failure indicated by significantly increasing costs such as those that are observable in many health insurance markets worldwide (OECD, 2015). Our results show, that costs (i.e., utility loss from monitoring) and benefits (i.e., access to insurance) need to be carefully considered in such discussions. To the best of our knowledge, this study is the first to provide an incentive-compatible quantification of utility losses from monitoring.

Hypothesis 3. Our third hypothesis states that the privacy discount ΔWTP is independent of the economic value of the insurance policy. The corresponding implication from this hypothesis for our experimental setup is that the transparency

⁵⁷ Using a similar risk elicitation task, Hansen, Jacobsen, and Lau (2016) find slightly higher but comparable results in their Danish household study with $\gamma = 0.68$ on average. Barseghy, Molinaro, O'Donoghue, and Teitelbaum (2013) also find evidence for probability weighting in insurance deductible choices.

⁵⁸ For example, the EU-wide eCall system, which dials the emergency number in case of a serious accident (Regulation (EU) 2015/758 of the European Parliament and of the Council, 2015). Furthermore, AIG Ireland urged the government to make telematics-based motor insurance mandatory for drivers under the age of 25 (Halpin, 2017). Further examples of such discussions can be found in life and health insurance where mandatory sharing of genetic test results is considered.

treatment effect of T_{20-8h} is larger than that of T_{30-8h} . This is because our main outcome variable is defined as WTP relative to the expected value of the insurance policy. If the absolute difference in WTP of the transparency treatments (i.e., T_{20-8h} or T_{30-8h}) to their respective control counterparts (i.e., C_{20} or C_{30}) were equal as implied by the third hypothesis, the relative measure would be larger under the low risk setting as the expected value of the insurance policy is lower here.⁵⁹ We thus test the Tobit estimates of the treatment effects of T_{20-8h} or T_{30-8h} in Appendix Table A for equality. While the sign of the difference is as expected under our third hypothesis (i.e., 0.233 larger transparency treatment effect under low risk setting), statistical significance is not given with p -value = 0.193. In summary, an absolute monetary valuation concept of privacy in line with the notion of privacy as a final good (Acquisti et al., 2016, p. 447) seems more likely to explain our data but cannot definitely be confirmed empirically. The reason why this does not translate into more severe profitability issues under the low-risk condition lies in the presence of probability weighting, which overcompensates this effect.

4.2 Heterogeneous treatment effects

Risk aversion as a dimension of heterogeneity in our context is motivated both by theoretical and empirical considerations. Theoretically, the disclosure of personal data to a principal comprises privacy risk, i.e., the risk that the personal data of the agent is collected unauthorized or misused as is broadly documented in cases of identity theft, invasion of privacy, or theft of payment information (Pan & Zinkhan, 2006). Higher aversion to risk then potentially correlates with the aversion to privacy risk. Empirical findings document this link to some extent, showing that risk aversion correlates positively with the required compensation for providing private data (Schudy & Utikal, 2017) and distrust in online retailers (Riquelme & Román, 2014), which in turn negatively impacts web-based transactions (Pan & Zinkhan, 2006), the disclosure of private information online (Bansal, Zahedi, & Gefen, 2016), and business-to-consumer internet exchanges (Cho, 2006).

We elicited risk preferences using the canonical binary lottery choice design. The left panel of Figure 4 shows the average proportion of safe choices in each of 4 times 10 original and scaled Holt and Laury (2002) binary lottery decisions. The right panel of Figure 4 then depicts the distribution of individual-level CRRA parameter estimates based on the RUM and RPM specification. Despite the fundamental differences in placing the error, we find similar explanatory power for our WTP measure and a decent

⁵⁹ Theoretically it is possible that the low-risk condition evokes higher privacy discounts in absolute terms relative to the high-risk condition, which could also result in a higher treatment effect of T_{20-8h} relative to T_{30-8h} . This would, however, be theoretically implausible and a test of equality of the treatment effects of T_{20-8h} and T_{30-8h} on absolute WTP cannot be rejected (p -value = 0.637).

level of rank-order correlation between RUM and RPM CRRA estimates (Spearman's $\rho = 0.888$, $p\text{-value} < 0.000$).⁶⁰

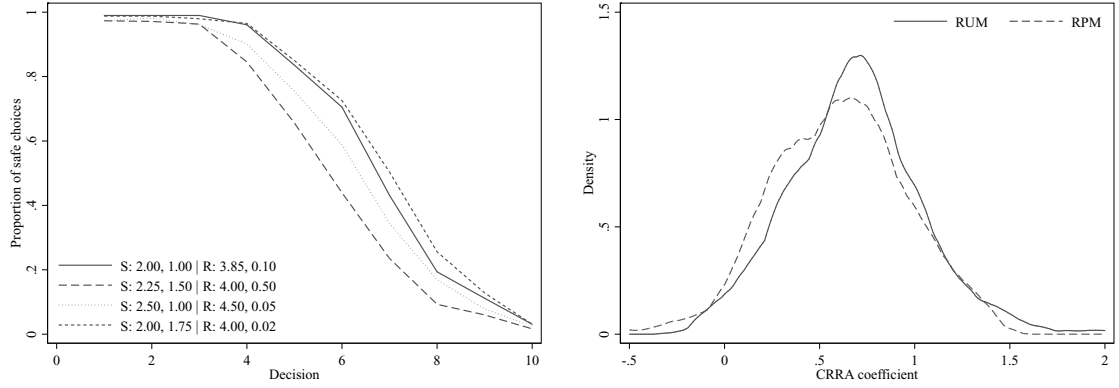


Figure 4. Average proportion of safe choices and CRRA coefficients density plots for RUM and RPM. *Notes:* The lines in the left panel indicate the different sets of scaled Holt and Laury (2002) lotteries with S indicating the safe option and R indicating the risky option. In the right panel, we show density plots of CRRA coefficients ρ of the functional form $U(Y) = \frac{Y^{1-\rho}}{1-\rho}$ for $Y > 0$. Random utility (RUM) with Fechner error and random parameter (RPM) models are estimated using maximum likelihood.

As a placebo test for the analysis of heterogeneous treatment effects with regard to risk aversion, we want to see whether our measures of risk aversion have explanatory power for WTP in our control conditions C_{20} and C_{30} . We find that a risk-averse subsample (i.e., in a sample split in half at median values for CRRA estimates from the RUM) is willing to pay 33.5 percent more ($p\text{-value} = 0.014$) in units of expected value from the insurance policy under the low-risk setting and 20.9 percent more ($p\text{-value} = 0.087$) under the high-risk setting compared to the less risk-averse subsample. The results from the RPM are comparable, though the differences are smaller. The positive and significant relationship between our RUM CRRA measure of risk aversion and WTP is also clearly visible in the top panel of Figure 5. What also becomes visible is the downward shift in WTP relative to the expected value of the insurance policy resulting from lower probability overweighting as an additional source of risk aversion under the high-risk condition (top right panel of Figure 5).

The lower panel of Figure 5 shows average treatment effects of sharing live location data conditional on the RUM CRRA coefficient of risk aversion.⁶¹ Within our largest treatment arm in terms of sample size—the low-risk condition (left panel of Figure 5)—we find that the relationship between risk aversion and the treatment effect of sharing live location data is to some extent hump-shaped. While the observed average treatment

⁶⁰ Because our maximum likelihood procedure had a higher success rate under the RUM (i.e., 84.3 percent versus 80.6 percent), we use the CRRA coefficients estimated on this basis for further analyses of heterogeneous treatment effects to increase power.

⁶¹ Using the plain share of risky choices among the 40 original and scaled Holt and Laury (2002) binary lottery decisions results in an almost identical picture.

effects seem to be driven most by the risk averse, the rather risk neutral participants also seem averse to sharing live location data. Among those sufficiently but not extremely risk averse, insurance has a positive value and the benefit of the insurance outweighs the disutility of privacy loss, thus, we observe treatment effects not distinguishable from zero in the range between 0.4 and 1.0 CRRA. Once risk aversion becomes sufficiently high (i.e., larger than 1.0 CRRA), the aversion to privacy risk seems to become more salient and eventually dominates the valuation. The increase in the treatment effect with increasing risk aversion is also present in the high-risk treatment arm; however, the effects are less precisely estimated and exhibit larger standard errors, which could be driven by the lower sample size (i.e., 192 versus 293). The differences in treatment effects among the rather risk neutral subjects between the low- and the high-risk condition remain a puzzle. Under the low-risk condition it seems that loss of privacy is more salient and outweighs the utility of the insurance coverage, which is limited for them anyway. However, under the high-risk condition, we cannot detect treatment effects of sharing live location data among the rather risk neutral.

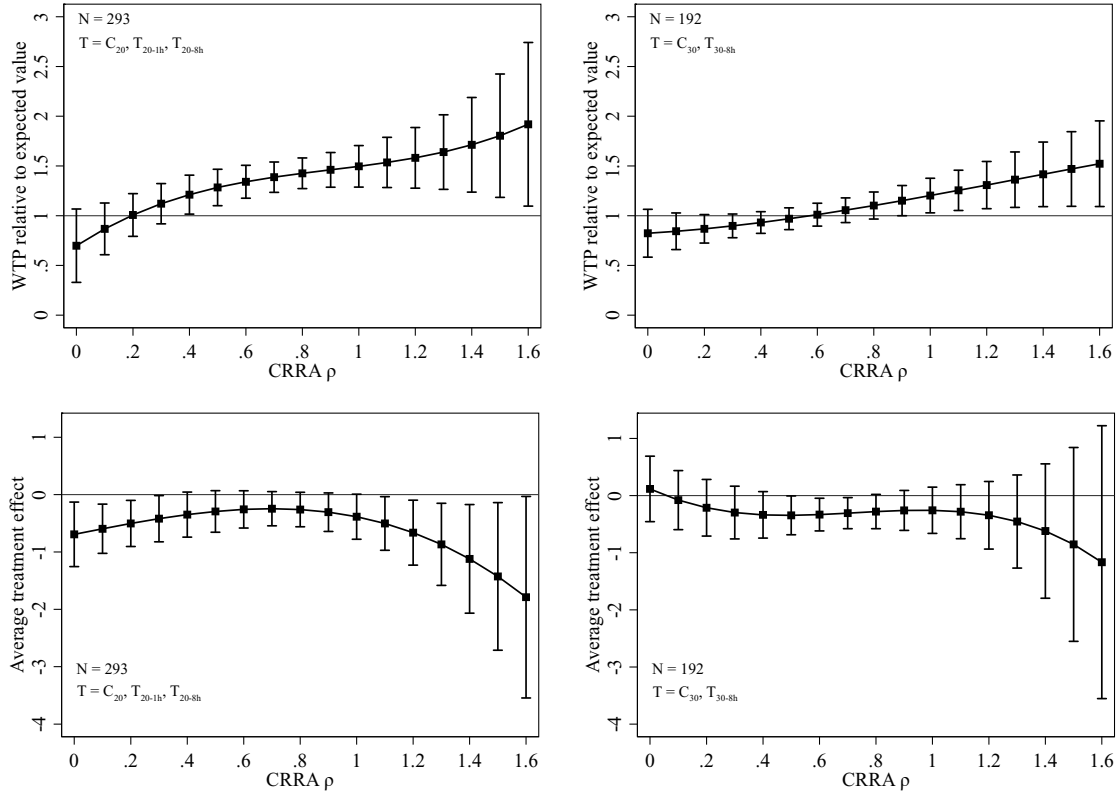


Figure 5. Relative WTP and average treatment effect conditional on risk aversion.

Notes: In the top panel we show pooled (i.e., low- (left panel) and high- (right panel) risk treatment conditions respectively) WTP relative to the expected value of the insurance policy conditional on RUM CRRA coefficients. In the lower panel we show average treatment effects (ATEs) of sharing live location data estimated from Tobit regressions conditional on RUM CRRA coefficients. All estimates are based on third-degree polynomials (in the lower panel interacting with either T_{20-1h} and T_{20-8h} (left) or T_{30-8h} (right)). Error bars indicate 95 percent confidence intervals based on clustered standard errors at the individual level.

In our experimental context, privacy risk (i.e., the risk of private data misuse) is likely perceived as low by the participants, which is why our estimates constitute a lower bound of the relationship between the privacy discount and risk aversion. In that sense, our experimental measure of a privacy discount rather represents an aversion to basic privacy disclosure than an aversion to privacy risk.

The treatment effects conditional on other dimensions of personal characteristics and personality are rather homogenous. Neither is gender a differentiating factor in explaining the observed treatment effects nor do aspects of personality (i.e., Big Five personality traits) and stated privacy preferences strongly determine the aversion to a loss of privacy in our experimental setup.⁶²

5 Conclusion

This paper quantifies the impact of digital monitoring on WTP for insurance in an incentive-compatible behavioral experiment. With the rise of new technologies, insurance companies increasingly use monitoring to condition contracts on observed behavior of agents instead of observed claims. While this mitigates potential issues resulting from information asymmetries such as moral hazard indicating welfare gains, agents assign a positive value to their privacy and thus experience a disutility from giving up privacy. The size of welfare loss from the loss of privacy in the insurance context is largely unexplored, but highly relevant to estimate total welfare effects from new technologies. We contribute to the limited empirical literature on the valuation of privacy by providing an incentive-compatible quantification of utility losses from monitoring.

Our experimental results suggest that agents care a great deal about their privacy. We find that the impact of mandatory sharing of live location data reduces the WTP relative to the expected value of an insurance policy by 25 to 50 percentage points, particularly threatening profitability for high-frequency risks where WTP falls below the expected value of the policy. The differential effects for different loss probabilities presumably lies in the fact that our experimental population adheres to a subjective concept of probability. The overweighting of small probabilities we document makes individuals more averse to low-frequency risks, in turn increasing willingness to pay relative to the economic value of the policy more for low-frequency than for high-frequency risks. While the disutility of sharing data is significant in economic terms, we also find that it is a function of the intensity of sharing data as we observe decreasing WTP with increasing duration of location data sharing. While an absolute monetary valuation concept of privacy (i.e., valuation of privacy is not conditional on the expected value of

⁶² The detailed results are available upon request.

the insurance policy) seems more likely to explain our data, we cannot clearly confirm this conjecture empirically. Heterogeneous treatment effects for risk preferences suggest higher treatment effects, that is, higher reductions in WTP caused by mandatory monitoring, for participants with higher levels of risk aversion (and also for some rather risk neutral participants). The very characteristic that drives WTP above the expected value of the policy—risk aversion—thus also causes WTP to decline when privacy concerns are involved.

Our findings have implications for insurance firms and policymakers. We show that a large fraction of the potential profit margin is marginalized by the discount agents demand to opt into a transparency contract. At the same time, transparency contracts reduce the costs implied by moral hazard and monitoring schemes could be used to promote prevention measures. Our results set a benchmark for the demand-side costs of transparency contracts that need to be contrasted with the benefits of using this technology. In the evaluation of potential mandatory data sharing regulations that could counteract market failure, policymakers need to consider individual welfare losses from giving up privacy. Current examples of such discussions can be found in life and health insurance where mandatory sharing of genetic test results is considered (Bélisle-Pipon, Vayena, Green, Cohen, 2019), or in auto insurance with mandatory use of telematic devices. Our results also have implications for classical results in the field of insurance economics. For example, in the context of Mossin's theorem (1968) stating that individuals fully insure at fair rates and demand less than full insurance at rates that include positive loadings, the use of monitoring devices implies that even at fair rates, insured demand less than full insurance if they are averse to privacy losses. Moreover, our results are complementary to the theoretical work of Gemmo et al. (2019) who analyze the impact of transparency contracts on market equilibria when there are two risk types.

The interpretation of our empirical results rests on a set of assumptions, since randomizing all potentially interesting influencing factors is hardly possible, creating room for future research. In our laboratory setting, participants were told that they would be sharing their location data with one anonymous PhD student at the University of St. Gallen, so our results cannot be transferred directly to a real-life insurance market setting, where a potentially large number of people would have access to the data. However, Schudy and Utikal (2017) show that the disutility increases with the number of recipients, indicating that utility losses as identified in our study are a lower benchmark. Our study focuses on the estimation of pure demand-side costs and our design is not intended to infer anything about welfare gains from potential behavioral change implied by

transparency contracts.⁶³ For example, leaving no room for asymmetric information, transparency contracts could be welfare increasing if the benefits of a lower premium due to behavioral changes outweigh the effort of the behavioral change. So far, we assume that transparency contracts measure risk types perfectly; further theoretical and empirical research should investigate the demand for transparency contracts when observed behavior is imperfectly correlated with risk type or when costs for the monitoring device are introduced. Our experimental setup is framed in an insurance context; however, in very generic terms as we do not specify the source of the risk (e.g., health, life, occupational, auto). Thus, there is room to investigate context-dependency of privacy discounts. In a related vein, we do not claim that our results are necessarily externally valid. Thus, field experiments are a natural next step. Furthermore, our setup could potentially be transferred to other contexts such as labor economics where there is some evidence on negative consequences of control on motivation (Falk & Kosfeld, 2006).

⁶³ The existing empirical evidence seems mixed. For example, Wouters and Bos (2000) document a positive influence of monitoring devices on driving behavior, while Heinzmann and Schade (2004) find no effect. Moreover, the influence seems to diminish over time (Bolderdijk, Knockaert, Steg, & Verhoef, 2011).

References

- Acquisti, A., Taylor, C. R., & Wagman, L. (2016). The economics of privacy. *Journal of Economic Literature*, 52(2), 1–64.
- Apesteguia, J., & Ballester, M. A. (2018). Monotone stochastic choice models: the case of risk and time preferences. *Journal of Political Economy*, 126(1), 74–106.
- Baillon, A. (2017). Bayesian markets to elicit private information. *Proceedings of the National Academy of Sciences*, 114(30), 7958–7962.
- Bansal, G., Zahedi, F. M., & Gefen, D. (2016). Do context and personality matter? Trust and privacy concerns in disclosing private information online. *Information and Management*, 53(1), 1–21.
- Barseghyan, L., Molinaro, F., O'Donoghue, T., & Teitelbaum, J. C. (2013). The nature of risk preferences: evidence from insurance choices. *American Economic Review*, 103(6), 2499–2529.
- Bélisle-Pipon, J.-C., Vayena, E., Green, R. C., & Cohen, I. G. (2019). Genetic testing, insurance discrimination and medical research: what the United States can learn from peer countries. *Nature Medicine*, 25(2019), 1198–1204.
- Benndorf, V., & Normann, H.-T. (2017). The willingness to sell personal data. *Scandinavian Journal of Economics*, 120(4), 1260–1278.
- Beresford, A. R., Kübler, D., & Preibusch, S. (2012). Unwillingness to pay for privacy: a field experiment. *Economic Letters*, 117(1), 25–27.
- Bolderdijk, J. W., Knockaert, J., Steg, E. M., & Verhoef E. T. (2011). Effects of pay-as-you-drive vehicle insurance on young drivers' speed choice: results of a Dutch field experiment. *Accident Analysis and Prevention*, 43(3), 1181–1186.
- Browne, M. J., & Kamiya, S. (2012). A theory of the demand for underwriting. *Journal of Risk and Insurance*, 79(2), 335–349.
- Charness, G., Eckel, C., Gneezy, U., & Kajackaite, A. (2018). Complexity in risk elicitation may affect the conclusions: a demonstration using gender differences. *Journal of Risk and Uncertainty*, 56(1), 1–17.
- Charness, G., Gneezy, U., & Imas, A. (2013). Experimental methods: eliciting risk preferences. *Journal of Economic Behavior and Organization*, 87, 43–51.
- Cho, J. (2006). The mechanism of trust and distrust formation and their relational outcomes. *Journal of Retailing*, 82(1), 25–35.
- Crocker, K. J., & Snow, A. (2011). Multidimensional screening in insurance markets with adverse selection. *Journal of Risk and Insurance*, 78(2), 287–307.
- Cummings, R. G., Harrison, G. W., & Rutström, E. E. (1995). Homegrown values and hypothetical surveys: is the dichotomous choice approach incentive-compatible? *American Economic Review*, 85(1), 260–266.
- Cummins, J. D., Phillips, R., & Lin, Y. (2006). Capital allocation and the pricing of financially intermediated risks: an empirical investigation, Working Paper.

- Cvrcek, D., Kumpost, M., Matyas, V., & Danezis, G. (2006). A study on the value of location privacy. *Online Proceedings of the Workshop on Privacy in the Electronic Society (WPES)*, 109–118.
- Dinev, T., & Hart, P. (2006). An extended privacy calculus model for E-Commerce transactions. *Information System Research*, 17(1), 61–80.
- Dohmen, T., Falk, A., Huffman, D., Sunde, U., Schupp, J., & Wagner, G. G. (2011). Individual risk attitudes: measurement, determinants, and behavioral consequences. *Journal of the European Economic Association*, 9(3), 522–550.
- Eckel, C. C., & Grossman, P. J. (2002). Sex differences and statistical stereotyping in attitudes toward financial risk. *Evolution and Human Behavior*, 23(4), 281–295.
- Eling, M., & Kraft, M. (2017). The impact of telematics on the insurability of risks, Working Paper.
- Falk, A., & Kosfeld, M. (2006). The hidden costs of control. *American Economic Review*, 96(5), 1611–1630.
- Feri, F., Giannetti, C., & Jentzsch, N. (2016). Disclosure of personal information under risk of privacy shocks. *Journal of Economic Behavior and Organization*, 123, 138–148.
- Gemmo, I., Browne, M. J., & Gründl, H. (2019). Privacy concerns in insurance markets: implications for market equilibria and social welfare. ICIR Working Paper Series No. 25.
- Gneezy, U., & Potters, J. (1997). An experiment on risk taking and evaluation periods. *Quarterly Journal of Economics*, 112(2), 631–645.
- Halpin, H. (2017). AIG wants to make telematics-based insurance mandatory for all drivers under 25. Retrieved from <http://www.thejournal.ie/telematic-insurance-aig-3667454-Oct2017/>, accessed 17 July 2018.
- Hansen, J. V., Jacobsen, R. H., & Lau, M. I. (2016). Willingness to pay for insurance in Denmark. *Journal of Risk and Insurance*, 83(1), 49–76.
- Harborth, D., & Pape, S. (2018). German translation of the Concerns for Information Privacy (CFIP) construct. Working Paper.
- Harrison, G. W., Johnson, E., McInnes, M. M., & Rutström, E. E. (2005). Risk aversion and incentive effects: comment. *American Economic Review*, 95(3), 897–901.
- Harrison, G. W., Lau, M. I., & Rutström, E. E. (2007). Estimating risk attitudes in Denmark: a field experiment. *Scandinavian Journal of Economics*, 109(2), 341–368.
- Harrison, G. W., & Ng, J. M. (2016). Evaluating the expected welfare gain from insurance. *Journal of Risk and Insurance*, 83(1), 91–120.
- Harrison, G. W., & Rutström, E. E. (2008). Risk aversion in the laboratory. In James C. Cox, Glenn W. Harrison (ed.) *Risk Aversion in Experiments* Emerald Group Publishing Limited, 12, 41–196.

- Heinzmann, H.-J., & Schade, F.-D. (2004). Prognosemöglichkeiten zur Wirkung von Verkehrssicherheitsmaßnahmen anhand des Verkehrszentralregisters. Berichte der Bundesanstalt für Straßenwesen, Reihe Mensch und Sicherheit, Heft M 155, Bergisch Gladbach.
- Hey, J. D., & Orme, C. (1994). Investigating generalizations of expected utility theory using experimental data. *Econometrica*, 62(6), 1291–1326.
- Holmström, B. (1979). Moral hazard and observability. *Bell Journal of Economics*, 10(1), 74–91.
- Holt, C. A., & Laury, S. K. (2002). Risk aversion and incentive effects. *American Economic Review*, 92(5), 1644–1655.
- Hoy, M. (1982). Categorizing risks in the insurance industry. *Quarterly Journal of Economics*, 97(2), 321–336.
- Hoy, M., & Ruse, M. (2005). Regulating genetic information in insurance markets. *Risk Management and Insurance Review*, 8(2), 211–237.
- Hui, K.-L., Teo, H. H., & Lee, S.-Y. T. (2007). The value of privacy assurance: an exploratory field experiment. *MIS Quarterly*, 31(1), 19–33.
- Insurance Europe (2015). European motor insurance markets: November 2015. Brussels.
- Jentzsch, N., Preibusch, S., & Harasser, A. (2012). Study on monetising privacy: an economic model for pricing personal information. European Network and Information Security Agency, Berlin.
- Kahneman, D., & Tversky, A. (1979). Prospect theory: an analysis of decision under risk. *Econometrica*, 4(2), 263–292.
- Mossin, J. (1968). Aspects of rational insurance purchasing. *Journal of Political Economy*, 76(4), 553–568.
- OECD (2015). Fiscal sustainability of health systems: bridging health and finance perspectives, OECD Publishing, Paris.
- Pan, Y., & Zinkhan, G. M. (2006). Exploring the impact of online privacy disclosures on consumer trust. *Journal of Retailing*, 82(4), 331–338.
- Pauly, M. V. (1968). The economics of moral hazard: comment. *American Economic Review*, 58(3), 531–537.
- Preibusch, S. (2013). Guide to measuring privacy concern: review of survey and observational instruments. Microsoft Research, Cambridge England.
- Prelec, D. (1998). The probability weighting function. *Econometrica*, 66, 95–113.
- Quiggin, J. (1982). A theory of anticipated utility. *Journal of Economic Behavior and Organization*, 3(4), 323–343.
- Rammstedt, B., & John, O. P. (2007). Measuring personality in one minute or less: a 10-item short version of the Big Five inventory in English and German. *Journal of Research in Personality*, 41, 203–212.

- Regulation (EU) 2015/758 of the European Parliament and of the Council (2015). Concerning type-approval requirements for the deployment of the eCall in-vehicle system based on the 112 service and amending Directive 2007/46/EC. Official Journal of the European Union.
- Riquelme, I. P., & Román, S. (2014). The relationships among consumers' ethical ideology, risk aversion and ethically-based distrust of online retailers and the moderating role of consumers' need for personal interaction. *Ethics and Information Technology*, 16(2), 135–155.
- Rothschild, M., & Stiglitz, J. (1976). Equilibrium in competitive insurance markets: an essay on the economics of imperfect information. *Quarterly Journal of Economics*, 90(4), 629–649.
- Smith, H. J., Milberg, S. J., & Burke, S. J. (1996). Information privacy: measuring individuals' concerns about organizational practices. *MIS Quarterly*, 20(2), 167–196.
- Schudy, S., & Utikal, V. (2017). 'You must not know about me' – on the willingness to share personal data. *Journal of Economic Behavior and Organization*, 141, 1–13.
- Tsai, J. Y., Egelman, S., Cranor, L., & Acquisti, A. (2011). The effect of online privacy information on purchasing behavior: an experimental study. *Information Systems Research*, 22(2), 254–268.
- Weller, J., Dieckmann, N. F., Tusler, M., Mertz, C. K., Burns, W., & Peters, E. (2013). Development and testing of an abbreviated numeracy scale: a Rasch analysis approach. *Journal of Behavioral Decision Making*, 26(2), 198–212.
- Wouters, P. I. J., & Bos, J. M. J. (2000). Traffic accident reduction by monitoring driver behaviour with in-car data recorders. *Accident Analysis and Prevention*, 32(5), 643–650.

Appendix A Tobit regression results

Table A. Treatment averages and treatment effects on relative WTP

<i>Treatment</i>	<i>Relative WTP</i>	<i>ATE</i>
Panel A: Low risk scenario		
C ₂₀	1.635*** (0.094)	
T _{20-1h}	1.380*** (0.110)	-0.254* (0.143)
T _{20-8h}	1.139*** (0.108)	-0.496*** (0.143)
Panel B: High risk scenario		
C ₃₀	1.093*** (0.058)	
T _{30-8h}	0.831*** (0.092)	-0.263** (0.109)

Notes: Column “Relative WTP” shows treatment averages of our relative WTP measure and column “ATE” shows average treatment effects; i.e., mean differences to the respective control group estimated from Tobit regressions including only the treatment dummies presented as explanatory variables. We rely on the Tobit model as our dependent variable, which is censored from below at 0 and above at 2.50 (1.67) in the low- (high-) risk conditions. This results from the censored range of WTP we presented to participants. In theory, it is possible that participants would be willing to pay more or even less than our range allows. Low- and high-risk conditions are estimated separately. Consistent with treatment assignment, all standard errors and tests are based on individual averages.

*** Significant at the 1 percent level.

** Significant at the 5 percent level.

* Significant at the 10 percent level.

Appendix B Experimental materials

The general instruction and the game instructions are provided in the next sections. Since the experiment was conducted in German, we present an English translation of the original instructions in German, which are available upon request.

B.1 General information

Welcome to our experiment! In this experiment you have to make economic decisions. The experiment is being conducted by a research group at the University of St. Gallen. Your participation is completely voluntary. You will receive a participation fee and can earn a considerable amount of money. The following description of the experiment should be easy to understand and you should read it carefully. Please take a few minutes to read it.

In today's experiment, we want you to play some economic games where you can earn a considerable amount of money. Your payout is determined by the decisions you make in these games. In addition to a participation fee of 4 EUR, you can earn between 2.02 EUR and 21.50 EUR.

The games are not meant to test you and there are no right or wrong answers. We are only interested in the way that you make economic decisions. It will take you approximately one hour to complete the experiment. The experiment is structured as follows:

- (1) Personal questionnaire.
- (2) One lottery game. (Game description will follow.)
- (3) Five short decision-making games. (Game description will follow.)
- (4) Additional personal questionnaire.

The information that we obtain will be used only for our research. It will be analyzed anonymously and will not be disclosed to third parties.

If at any time or for any reason you decide not to participate, you are free to leave whether we have started the experiment or not. If you already know that you cannot stay for the entire hour, please let us know immediately.

Please do not talk or communicate with other participants during the experiment. Also, please turn off your mobile phone. You can always contact the research assistants by raising your hand if you have questions or need further explanation.

Thank you in advance for your effort and time.

B.2 Overview compensation

During this experiment you will play six short decision-games where you can earn money in addition to your participation fee. The decisions you make in each of the six games will influence your earnings at the end of the experiment. The payout consists of the following three blocks:

- (1) Participation fee in the amount of 4 EUR.
- (2) Earnings of the first lottery game (maximum 4.50 EUR, minimum 0.02 EUR)
- (3) Earnings of one of the five economic decision-making games (maximum 17 EUR, minimum 2 EUR). We will randomly determine the game for payout by rolling a die.

In addition to your participation fee, you can earn between 2.02 EUR and 21.50 EUR today. Since the decision-making games have different temporal dimensions, the payout will be made tomorrow. The amount of the payment will be announced to you immediately after the experiment.

B.3 Introduction first lottery game

We now begin the first game. In the following, we will explain its structure. Your understanding of the procedure is very important.

You have to make 40 decisions between two lotteries. Each of the decisions has the following structure: We roll a 10-sided die to determine your payout. Please decide in each line which lottery (A or B) you would prefer to play:

Lottery A

2 EUR, if the die is 1.
1.60 EUR, if the die is 2-10.

Lottery B

3.85 EUR, if the die is 1.
0.10 EUR, if the die is 2-10.

For example, if you choose Lottery A and the die shows a 5 then you would win 1.60 EUR. If you chose lottery B, you would win 0.10 EUR. If the die shows a 1 then you would win 2 EUR (lottery A) or 3.85 EUR (lottery B).

The 40 decisions are presented on four tables with ten decisions each. Each table is displayed on one page. You make your decision by clicking on the lottery you would prefer to play.

At the end of the experiment, one of the 40 decisions will be drawn for payout. We will throw a 6-sided die, which is rolled until a 1, 2, 3 or 4 is shown. The number determines the decision table. Afterwards, we roll a 10-sided die twice to determine which decision is relevant for payout (first die roll) and which amount is paid out (second die roll). Each decision has the same probability to be drawn for payout. Please note: The amounts displayed are the same for each table; only the probabilities change per decision.

B.4 Decisions first lottery game

Table B.4.1. Lottery table 1

<i>Lottery A</i>	<i>Lottery B</i>
2.00 EUR, if the die is 1.	3.85 EUR, if the die is 1.
1.60 EUR, if the die is 2-10.	0.10 EUR, if the die is 2-10.
2.00 EUR, if the die is 1-2.	3.85 EUR, if the die is 1-2.
1.60 EUR, if the die is 3-10.	0.10 EUR, if the die is 3-10.
2.00 EUR, if the die is 1-3.	3.85 EUR, if the die is 1-3.
1.60 EUR, if the die is 4-10.	0.10 EUR, if the die is 4-10.
2.00 EUR, if the die is 1-4.	3.85 EUR, if the die is 1-4.
1.60 EUR, if the die is 5-10.	0.10 EUR, if the die is 5-10.
2.00 EUR, if the die is 1-5.	3.85 EUR, if the die is 1-5.
1.60 EUR, if the die is 6-10.	0.10 EUR, if the die is 6-10.
2.00 EUR, if the die is 1-6.	3.85 EUR, if the die is 1-6.
1.60 EUR, if the die is 7-10.	0.10 EUR, if the die is 7-10.
2.00 EUR, if the die is 1-7.	3.85 EUR, if the die is 1-7.
1.60 EUR, if the die is 8-10.	0.10 EUR, if the die is 8-10.
2.00 EUR, if the die is 1-8.	3.85 EUR, if the die is 1-8.
1.60 EUR, if the die is 9-10.	0.10 EUR, if the die is 9-10.
2.00 EUR, if the die is 1-9.	3.85 EUR, if the die is 1-9.
1.60 EUR, if the die is 10.	0.10 EUR, if the die is 10.
2.00 EUR, if the die is 1-10.	3.85 EUR, if the die is 1-10.

Table B.4.2. Lottery table 2

<i>Lottery A</i>	<i>Lottery B</i>
2.25 EUR, if the die is 1.	4.00 EUR, if the die is 1.
1.50 EUR, if the die is 2-10.	0.50 EUR, if the die is 2-10.
2.25 EUR, if the die is 1-2.	4.00 EUR, if the die is 1-2.
1.50 EUR, if the die is 3-10.	0.50 EUR, if the die is 3-10.
2.25 EUR, if the die is 1-3.	4.00 EUR, if the die is 1-3.
1.50 EUR, if the die is 4-10.	0.50 EUR, if the die is 4-10.
2.25 EUR, if the die is 1-4.	4.00 EUR, if the die is 1-4.
1.50 EUR, if the die is 5-10.	0.50 EUR, if the die is 5-10.
2.25 EUR, if the die is 1-5.	4.00 EUR, if the die is 1-5.
1.50 EUR, if the die is 6-10.	0.50 EUR, if the die is 6-10.
2.25 EUR, if the die is 1-6.	4.00 EUR, if the die is 1-6.
1.50 EUR, if the die is 7-10.	0.50 EUR, if the die is 7-10.
2.25 EUR, if the die is 1-7.	4.00 EUR, if the die is 1-7.
1.50 EUR, if the die is 8-10.	0.50 EUR, if the die is 8-10.
2.25 EUR, if the die is 1-8.	4.00 EUR, if the die is 1-8.
1.50 EUR, if the die is 9-10.	0.50 EUR, if the die is 9-10.
2.25 EUR, if the die is 1-9.	4.00 EUR, if the die is 1-9.
1.50 EUR, if the die is 10.	0.50 EUR, if the die is 10.
2.25 EUR, if the die is 1-10.	4.00 EUR, if the die is 1-10.

Table B.4.3. Lottery table 3

<i>Lottery A</i>	<i>Lottery B</i>
2.50 EUR, if the die is 1.	4.50 EUR, if the die is 1.
1.00 EUR, if the die is 2-10.	0.05 EUR, if the die is 2-10.
2.50 EUR, if the die is 1-2.	4.50 EUR, if the die is 1-2.
1.00 EUR, if the die is 3-10.	0.05 EUR, if the die is 3-10.
2.50 EUR, if the die is 1-3.	4.50 EUR, if the die is 1-3.
1.00 EUR, if the die is 4-10.	0.05 EUR, if the die is 4-10.
2.50 EUR, if the die is 1-4.	4.50 EUR, if the die is 1-4.
1.00 EUR, if the die is 5-10.	0.05 EUR, if the die is 5-10.
2.50 EUR, if the die is 1-5.	4.50 EUR, if the die is 1-5.
1.00 EUR, if the die is 6-10.	0.05 EUR, if the die is 6-10.
2.50 EUR, if the die is 1-6.	4.50 EUR, if the die is 1-6.
1.00 EUR, if the die is 7-10.	0.05 EUR, if the die is 7-10.
2.50 EUR, if the die is 1-7.	4.50 EUR, if the die is 1-7.
1.00 EUR, if the die is 8-10.	0.05 EUR, if the die is 8-10.
2.50 EUR, if the die is 1-8.	4.50 EUR, if the die is 1-8.
1.00 EUR, if the die is 9-10.	0.05 EUR, if the die is 9-10.
2.50 EUR, if the die is 1-9.	4.50 EUR, if the die is 1-9.
1.00 EUR, if the die is 10.	0.05 EUR, if the die is 10.
2.50 EUR, if the die is 1-10.	4.50 EUR, if the die is 1-10.

Table B.4.4. Lottery table 4

<i>Lottery A</i>	<i>Lottery B</i>
2.00 EUR, if the die is 1.	4.00 EUR, if the die is 1.
1.75 EUR, if the die is 2-10.	0.02 EUR, if the die is 2-10.
2.00 EUR, if the die is 1-2.	4.00 EUR, if the die is 1-2.
1.75 EUR, if the die is 3-10.	0.02 EUR, if the die is 3-10.
2.00 EUR, if the die is 1-3.	4.00 EUR, if the die is 1-3.
1.75 EUR, if the die is 4-10.	0.02 EUR, if the die is 4-10.
2.00 EUR, if the die is 1-4.	4.00 EUR, if the die is 1-4.
1.75 EUR, if the die is 5-10.	0.02 EUR, if the die is 5-10.
2.00 EUR, if the die is 1-5.	4.00 EUR, if the die is 1-5.
1.75 EUR, if the die is 6-10.	0.02 EUR, if the die is 6-10.
2.00 EUR, if the die is 1-6.	4.00 EUR, if the die is 1-6.
1.75 EUR, if the die is 7-10.	0.02 EUR, if the die is 7-10.
2.00 EUR, if the die is 1-7.	4.00 EUR, if the die is 1-7.
1.75 EUR, if the die is 8-10.	0.02 EUR, if the die is 8-10.
2.00 EUR, if the die is 1-8.	4.00 EUR, if the die is 1-8.
1.75 EUR, if the die is 9-10.	0.02 EUR, if the die is 9-10.
2.00 EUR, if the die is 1-9.	4.00 EUR, if the die is 1-9.
1.75 EUR, if the die is 10.	0.02 EUR, if the die is 10.
2.00 EUR, if the die is 1-10.	4.00 EUR, if the die is 1-10.

B.5 Exemplary introduction of the T_{20-1h} insurance game condition

Let us move on to the next game. In the following, we will explain its structure. Your understanding of the procedure is very important.

Your endowment in this game is 17 EUR. You are at risk of losing 15 EUR of your 17 EUR endowment. The loss occurs in 2 of 10 cases, or a 20 percent probability, but you can buy insurance against this loss.

On the next page you have to decide for 15 different prices, whether you want to buy insurance that fully compensates you for the loss of 15 EUR [an exemplary decision table is presented in Appendix B.6]. By purchasing the insurance, you agree to share your WhatsApp GPS live status with us for 1 hour at the end of the experiment.

If this insurance game is selected for payout at the end of the experiment, one of your 15 decisions will be randomly drawn for payout. The amount is determined by your decision. We use a 20-sided die, which is rolled until a number between 1 and 15 appears. If you have chosen to buy insurance, your payout will be 17 EUR minus the insurance premium. For example, if the insurance premium is 1 EUR, you will receive 16 EUR. In addition, you have to share your WhatsApp GPS live status with us for 1 hour.

To share your WhatsApp GPS live status, you will receive a mobile phone number from us at the end of the experiment. Before leaving the laboratory, you will start sharing your location data for 1 hour with this number. This is a standard WhatsApp feature. For 1 hour, a research assistant in St. Gallen will monitor your whereabouts to ensure that you are still sharing your location data. After that hour has elapsed, the live sharing will stop automatically and your number will be deleted from our phones. If you have

not chosen to buy insurance in the selected decision, we will roll a 10-sided die to determine whether or not you will lose 15 EUR.

B.6 Decisions insurance game

Table B.6. Insurance decision table

	I would buy insurance	I would not buy insurance
If the premium is 0.50 EUR...	O	O
If the premium is 1.00 EUR...	O	O
If the premium is 1.50 EUR...	O	O
If the premium is 2.00 EUR...	O	O
If the premium is 2.50 EUR...	O	O
If the premium is 3.00 EUR...	O	O
If the premium is 3.50 EUR...	O	O
If the premium is 4.00 EUR...	O	O
If the premium is 4.50 EUR...	O	O
If the premium is 5.00 EUR...	O	O
If the premium is 5.50 EUR...	O	O
If the premium is 6.00 EUR...	O	O
If the premium is 6.50 EUR...	O	O
If the premium is 7.00 EUR...	O	O
If the premium is 7.50 EUR...	O	O

B.7 Privacy questionnaire

Table B.7. CFIP instrument to measure privacy concerns (7-point Likert scale)

#	Item
1	It usually bothers me when companies ask me for personal information.
2	When companies ask me for personal information, I sometimes think twice before providing it.
3	It bothers me to give personal information to so many companies.
4	I am concerned that companies are collecting too much personal information about me.
5	All the personal information in computer databases should be double-checked for accuracy – no matter how much this costs.
6	Companies should take more steps to make sure that the personal information in their files is accurate.
7	Companies should have better procedures to correct errors in personal information.
8	Companies should devote more time and effort to verifying the accuracy of the personal information in their databases.
9	Companies should not use personal information for any purposes unless it has been authorized by the individuals who provided the information.
10	When people give personal information to a company for some reason, the company should never use the information for any other reason.
11	Companies should never sell the personal information in their computer databases to other companies.
12	Companies should never share personal information with other companies unless it has been authorized by the individuals who provided the information.
13	Companies should devote more time and effort to preventing unauthorized access to personal information.
14	Computer databases that contain personal information should be protected from unauthorized access – no matter how much it costs.
15	Companies should take more steps to make sure that unauthorized people cannot access personal information in their computers.

B.8 Numeracy tasks

Table B.8. Numeracy questionnaire

#	Item
1	Imagine that we flip a fair coin 1000 times. Out of 1000 throws, how many times do you think the coin would come up as heads?
2	In the Bingo Lottery, the chances of winning a 10 EUR prize are 1 percent. What is your best guess about how many people would win a 10 EUR prize if 1000 people each buy a single ticket from the Bingo Lottery?
3	In a raffle, the chance of winning a car is 1 in 1000. What percent of tickets of the raffle win a car?
4	If the chance of getting a disease is 10 percent, how many people would be expected to get the disease? Out of 1000?
5	If the chance of getting a disease is 20 out of 100, this would be the same as having a _____ percent chance of getting the disease.
6	A bat and a ball cost \$1.10 in total. The bat costs \$1.00 more than the ball. How much does the ball cost?
7	In a lake, there is a patch of lily pads. Every day, the patch doubles in size. If it takes 48 days for the patch to cover the entire lake, how long would it take for the patch to cover half of the lake?
8	Suppose you have a close friend who has a lump in her breast and must have a mammography. Of 100 women like her, 10 of them actually have a malignant tumor and 90 of them do not. Of the 10 women who actually have a tumor, the mammogram indicates correctly that 9 of them have a tumor and indicates incorrectly that 1 of them does not. Of the 90 women who do not have a tumor, the mammogram indicates correctly that 80 of them do not have a tumor and indicates incorrectly that 10 of them do have a tumor. The table below summarizes all of this information. Imagine that your friend tests positive (as if she had a tumor), what is the likelihood that she actually has a tumor?

	Mammogram indicates "has a tumor"	Mammogram indicates "has not a tumor"	Total
Has a tumor	9	1	10
Has not a tumor	10	80	90
Total	19	81	100

Essay III: Utilization of input factors in the German property and casualty insurance industry

Abstract

We analyze the input utilization in the German property and casualty insurance industry in a newly constructed sample of firm-level data in the period 1956–2015. A study for the U.S. (Cummins & Nini, 2002) finds that property and casualty insurers over-utilize capital and labor. Compared to the study by Cummins and Nini (2002), our large historical dataset exhibits less heterogeneity and allows a cleaner identification and analysis of the impact of firm characteristics on the utilization of input factors. Furthermore, we extend the results by explicitly investigating the firm characteristics driving the utilization of labor. We apply data envelopment analysis (DEA) to determine the optimal mix of business inputs to produce a given amount of outputs in comparison to the best-in-class firm(s). We find that German p/c insurers have substantial potential for cost saving and that labor input is the main driver of their inefficiency. Moreover, we find severe differences in firm characteristics driving the utilization of labor. With respect to the utilization of equity, we confirm most of the findings from Cummins and Nini (2002) for our sample period and German p/c insurers.

Keywords

Insurance, multi-stage data envelopment analysis, input utilization

Martin Eling, Martin Lehmann, Philipp Schaper (2020).

This paper was presented at the 2019 Risk and the Insurance Business in History conference in Seville, the 2019 23rd International Congress on Insurance: Mathematics and Economics in Munich, and the 2019 Ph.D. in Finance Seminar at the University of St. Gallen.

1 Introduction

A large stream of literature has investigated the productivity and efficiency of the insurance industry (e.g., Cummins & Nini, 2002; Cummins & Xie, 2008, for the U.S. and Hussels & Ward, 2007; Luhnen, 2009; Trigo-Gamarra & Growitsch, 2010, for Germany). In this context and in other parts of the academic literature the optimal amount of equity capital (e.g. Eling, Schmeiser, & Schmit, 2007) has been critically discussed. Cummins and Nini (2002) investigate the large increase of equity capital in the U.S. property and casualty (p/c) insurance industry during the 1990s and find that insurers significantly use too much equity capital compared to how much equity capital they should be using based on efficiency considerations. They document that insurers use too much labor, capital, and business services. One of their main results is that the use of equity capital is inefficient and not a rational response to market conditions.

The aim of this paper is to analyze the input utilization of insurance companies in a large historical dataset which exhibits less heterogeneity than the U.S. data considered so far. We analyze input utilization in the German non-life insurance industry with firm-level data from 1956 to 2015. The extremely long sample period allows us to analyze unrevealed questions regarding input utilization in the insurance industry. Especially, it allows analyzing the impact of the business environment on the utilization of inputs. Given the recent trends towards market consolidation, one might expect a reduction in the over-utilization of input factors over time, which needs to be revealed empirically.⁶⁴ With the computerization and digitalization of the insurance industry, one may expect that capital becomes more and labor less important.

Our paper contributes to the ongoing debate of utilization of equity capital and labor in a competitive market environment (e.g., Cummins & Nini, 2002). We employ frontier efficiency methodologies, which analyze efficiency based on a benchmark mechanism that compares firms against best-in-class firms. These efficiency methodologies allow us to determine the optimal mix of business inputs to produce a given amount of outputs in comparison to best-in-class firms. The unusual long time period considered in our analysis allows us to assess the impact of the business. We believe that we are among the first to focus on the usage of input factors. Cummins and Nini (2002) investigate the usage of equity capital (but not labor) after the introduction of the U.S. risk-based capital standards.

⁶⁴ Related papers are Cummins and Rubio-Misas (2006) who analyze the impact of the European wide deregulation on the Spanish insurance industry in the period 1989–1998. Their results show that many small, inefficient, financially underperforming insurance firms vanished, and the overall market has become more productive. Eling and Schaper (2017) find that adverse business conditions force managers to conduct more productivity-enhancing activities (e.g., cost-savings programs) and that some European life insurers over-utilize equity capital between 2002–2013.

Our research sheds light on the development of labor and capital usage for an important subsector of the economy.⁶⁵ Given the recent use of technology in the insurance industry (see e.g., Eling & Lehmann, 2018) and questions on future labor needs (see e.g., Johansson & Vogelgesang, 2015; Malhotra, 2015; Deloitte, 2018), our analysis not only covers an important and widely unexplored field, but is also highly relevant for insurance managers and public policy.

The remainder of this paper is structured as follows. In Section 2, we review the literature on efficiency measurement and input utilization. Section 3 presents our hypotheses with respect to labor. Section 4 outlines the methodology and data. In Section 5, we discuss the empirical results and Section 6 concludes.

2 Literature review

Scholars have often investigated the cost efficiency of insurance companies and documented substantial potential for cost saving considering aggregated efficiency numbers. For example, Luhnén (2009) finds that German p/c insurers could save on average 52 percent in costs for 1995–2006. For the period 1991–2006, Mahlberg and Url (2010) report even higher results for German insurance groups: 60 percent on average. For the German life insurance industry, Hussels and Ward (2007) and Trigo-Gamarra and Growitsch (2010) find average potential cost savings of 44 percent and 52 percent for 1991–2002 and 1997–2005, respectively. In their cross-European sample of life insurers, Eling and Schaper (2017) report a 43 percent cost saving potential. Similar levels of cost inefficiency have been reported for the U.S. insurance industry (e.g., Cummins & Nini, 2002; Cummins & Xie, 2008). Researchers have analyzed the impact of specific firm factors (e.g., size, distribution channel, ownership, premium growth, internationalization) and environmental changes on efficiency values (Cummins & Rubio-Misas, 2006; Cummins & Xie, 2008; Luhnén, 2009; Eling & Luhnén, 2010; Mahlberg & Url, 2010; Biener, Eling, & Wirfs, 2016; Eling & Schaper, 2017).

So far, studies have not analyzed how specific inputs (i.e., capital and labor) are utilized and how they individually drive cost (in-)efficiency. To the best of our knowledge, only Cummins and Nini (2002) have analyzed specific firm factors driving the utilization of equity for the U.S. p/c insurance industry. They motivate their study with the rise of capitalization in the U.S. p/c insurance market during the 1990s. Cummins and Nini (2002) investigate whether the increase was a valid response to structural changes (e.g., due to the introduction of risk-based capital standards, the increasing attention to

⁶⁵ Global insurance premiums are USD 5.2 trillion in 2018, accounting for 6.1 percent of the global GDP. The German insurance market has premiums of USD 241 billion (145 billion non-life, 96 billion life), which is 6.03 percent of the German GDP. See Staib, Puttaiah, and Tschekassin (2019).

financial ratings or the more volatile business structure⁶⁶) or if the rising capital levels are a true inefficiency leading to decreased performance. As their analysis of the impact of specific firm factors on the use of equity capital is the foundation for the development of hypotheses in this paper, we briefly present their hypotheses.

Financial distress – Insurers hold equity capital to ensure solvency. Cummins and Nini (2002) argue that the probability of insolvency is related to an insurer's ability to diversify risk. They consider four measures of diversification. Three of them (diversification by line of business, geographical diversification, use of reinsurance) measure liability risk and one (percentage of risky assets) measures asset risk. The volatility of the return on equity (ROE) is considered as a comprehensive measure taking underwriting and investment risk into account. The authors argue that firms with lower risk use less capital. In the context of financial distress and in relation to diversification, Cummins and Nini (2002) argue that large insurers can predict the average loss in their insurance pool more precisely (law of large numbers), so that they should be less prone to insolvency and less sensitive to large losses. Consequently, firm size should be inversely related to the utilization of equity capital.

Conflicts of interest – In the insurance industry, there are two type of ownership forms—mutual and stock insurers—which make it possible to analyze conflicts between owners and managers,⁶⁷ and owners and policyholders⁶⁸. In mutual insurers, the owner and the policyholder are the same. This suggests some potential for owner–manager conflict for mutual insurers to use less equity capital than stock insurers. Moreover, mutual insurers may need less capital as they invest in less complex projects. However, these effects could be offset by mutuals' less access to capital markets (Cummins & Nini, 2002). Cummins and Nini (2002) are ambiguous about the differences in capital utilization between the two organizational forms. In addition, managers control the paid premium of the policyholder between the time of premium payment and claim settlement. Risks with long settlement horizons allow managers to invest in projects they are profiting from. Like an owner–manager conflict, this situation can be resolved by reducing the

⁶⁶ Over the years and decades, the options for insurance customers to diversify their risk have increased. Thus, they may hedge the more predictable risks by themselves and only use insurance for the more volatile risks (Cummins & Nini, 2002).

⁶⁷ The owner–manager conflict exists because managers may have an incentive to take on extra risk that would increase their salary, but not necessarily the value of equity. However, to take on risky projects, managers need cash and available equity capital. Limiting the amount of equity would align the interests of owners and managers (Cummins & Nini, 2002).

⁶⁸ If policyholders and owners were two separate groups, the owner–policyholder conflict exists, because policyholders are paid first, and owners share the profit, which goes beyond the policyholders' payments. In this situation, the liability of owners is limited, and they have an interest in risky projects (in line with managers incentives). However, this behavior is anticipated by policyholders and would decrease their willingness to pay for insurance. Thus, the insurers use equity capital to insure solvency to policyholders.

amount of equity in firms with longer tailed business. A third potential conflict of interest arises from the information asymmetry between investors and managers. As p/c insurers have actuarial and accounting flexibility in estimating the claim reserves, investors may never know the true value of loss reserves. So, firms with greater information asymmetries might accumulate equity during profitable periods. However, as Cummins and Nini (2002) argue, these firms might not have the same access to the capital market and as a result, they use less equity capital.

Growth opportunities and product market interactions – Cummins and Nini (2002) argue that insurers that want to grow are expected to hold more equity capital to avoid raising expensive capital in the future. Moreover, they argue that insurers, which operate mainly in the commercial lines hold more equity capital because commercial customers are seeking financial stability and have low costs of switching their insurer.

Table 8 summarizes the findings from Cummins and Nini (2002), focusing on firm factors and equity utilization. The role of technology is not considered as a driver for capital usage. We might expect that more technology-prone insurers, *ceteris paribus*, will use more capital and less labor.

Table 8. Hypotheses and results from Cummins and Nini (2002)

<i>Hypothesis</i>	<i>Result</i>
Financial distress	
The Herfindahl indices of premiums written by state and by line of business will be positively related to capital utilization.	Not supported
Firms with higher ratios of ceded loss reserves to direct plus assumed loss reserves will use less capital	Supported
Firms with higher percentages of assets invested in stocks and real estate will use more capital.	Supported
Higher risk, as measured by the standard deviation of ROE, will be associated with higher capital utilization.	Not supported
Capitalization will be inversely related to firm size.	Supported
Conflicts of interest	
Mutuals will not utilize capital more or less intensively than stocks.	Mutuals use less equity.
The ratio of reserves to losses incurred will be inversely related to capital utilization.	Supported
Firms with higher information asymmetries between managers and owners will be more highly leveraged than firms with lower information asymmetries.	Supported
Growth opportunities and product market interactions	
Firms with more growth opportunities will hold relatively more equity capital.	Not supported
Capitalization will be inversely related to the percentage of an insurer's revenues coming from personal lines of insurance.	Supported

3 Evidence on labor utilization and hypotheses development

We extend Cummins and Nini's (2002) work by analyzing the utilization of labor for our German sample. As providing services to the insured is labor intense, labor expenses are the main part of the operating expense in insurance firms and are potentially another source of cost inefficiency.⁶⁹ Moreover, as most technological advances have either replaced or are complementing their employees, labor expenses probably offer the most room for improvement. Indeed, Cummins and Nini (2002) find that U.S p/c insurers significantly use too much equity capital (85.8 percent), but also use too much labor by 159.7 percent.

Efficiency values are the result of a benchmark comparison. Assuming an input orientation, the focus of firms is to minimize the inputs (costs) to produce a given amount of outputs. Given fixed input prices, cost inefficiencies arise because firms use a higher amount of input than the best-practice firm(s). We also derive the utilization values from a best-practice comparison. As mentioned before, insurers hold equity capital to prove their solvency. Consequently, this should not offer insurers a lot of room for improvement; insurers with similar insurance business should utilize similar amounts of equity capital. This has been even more strictly enforced by the regulator through Solvency I and Solvency II. The results by Cummins and Nini (2002) (regarding the utilization of equity) may be explained by the different period and may be driven by the firm characteristics they investigate later in their analysis. However, they show that labor is the most utilized input. In our view, only labor could explain the high cost saving potential in the insurance industry as it offers the most flexibility.

There are several plausible reasons for the use of labor in insurance firms. One reason is that insurers need many different job profiles with specific knowledge along their value chain. Often, as the tasks are very specific and require different personal skills; they cannot be combined in a comprehensive job profile. This means that insurers need to hire a variety of job profiles.

Another reason is that the German p/c insurance industry was highly regulated until the mid-1990s. The national insurance markets had previously been closed to other European competitors, which restricted the competition in each country. With the third generation of insurance directives, established in 1994, insurers have been allowed to operate with one single license in the whole European Economic Area (Hussel & Ward, 2007; Mahlberg & Url, 2010). Therefore, competition increased, and insurers

⁶⁹ According to Cummins and Weiss (2013), for U.S. non-life insurers, 76.6 percent of operating expenses are for human services (i.e., labor expenses). For the Spanish insurance industry, Cummins, Rubio-Misas, and Zi (2004) report that labor accounts for 67 percent of non-loss expenses.

have become more efficient and productive.⁷⁰ Prior to that, the German p/c insurance industry had felt no competitive pressure due to their stable premium income and investment return. However, following the concept of X-efficiency by Leibenstein (1966), the absence of competitive pressure could result in less motivated staff and inefficient firms. Moreover, as managers often have an incentive to expand the business, the limited competition may have induced the hiring of more employees than needed.

In addition, technological improvements over the last decades may also have consistently transformed the production process in the insurance industry. Through automatization and standardization of processes, the insurers may have more personnel than needed. Under Germany's strong labor laws, unions and work councils in larger firms, reducing the workforce is quite complicated.⁷¹ Recent technological trends (e.g., big data, internet of things, artificial intelligence) may even further increase the over-utilization of labor.

In conclusion, we expect the utilization of labor to be the main driver of insurers' cost inefficiency. Due to technological developments and Germany's strong labor protection mechanisms, the utilization may have increased over the years. We state our first hypothesis as follows:

Hypothesis 1: *Labor utilization is the main driver of cost inefficiency.*

Based on insurance efficiency studies and results from other industries, we derive our hypotheses regarding the influence of firm variables on labor utilization. With respect to labor utilization there is, to the best of our knowledge, no specific empirical evidence from insurance research.

We have argued before that labor utilization may be one source of German p/c insurers' inefficiency. However, we expect differences in the utilization of labor among insurers. In our view, there could be many explanations for the heterogenous use of labor. For example, some insurers may see an advantage in optimizing the capacity of their workforce, they have better possibilities to train and educate their staff, or they have better access to more motivated and educated personnel. Therefore, insurers which can create an optimal working environment for their employees, have a competitive advantage. In the remainder of this section, we discuss firm characteristics, which may influence the utilization of labor.

⁷⁰ However, the empirical results are mixed. The results from Luhn (2009) support that deregulation lead to an efficiency increase. Mahlberg and Url (2010) do not find that inefficient insurers improved their position after the deregulation significantly, but they improved their allocative efficiency, i.e., they use the right input mix.

⁷¹ For example, 33 percent (50 percent) of the supervisory board consist of employee representatives, if the firm has less (more) than 2,000 employees. We think that these laws limit the flexibility to lay off (many) employees.

Size – From manufacturing industry studies, there is evidence of the relation between firm size and labor efficiency. For example, in a five-country OECD study, van Ark and Monnikhof (1996) find that in 1990, an employee in a German manufacturer with 500 or more employees produced 12.2 percent more output than an average employee in the whole sample. In contrast, an employee in a small firm (0–9 employees) produced 22.9 percent less output than an average employee. Van Ark and Monnikhof (1996) find similar results for the years 1967 and 1977 and for France, the U.K., the U.S. and Japan. Leung, Meh, and Terajima (2008) confirm the results and find a positive link between firm size and labor productivity for Canadian and U.S. non-manufacturing firms, but they excluded the financial service industry. To date, the efficient use of labor in the insurance industry has not been studied. However, from general efficiency studies (which do not differentiate between the inefficient use of inputs) we know that large insurers tend to be more efficient (Cummins & Zi, 1998; Cummins & Rubio-Misas, 2006; Eling & Luhnen, 2010).

Larger firms may profit from economies of scale. With respect to labor, every firm needs some overhead employees, which of course increase in number when the company is growing. However, if the overhead does not grow at the same scale as the output-generating employees (e.g., sales agents, asset managers), larger firms can more easily finance their overhead as their relative costs decrease. Moreover, large insurers may find it easier to centralize certain jobs (e.g., claims management and settlement) and to redistribute the work. Consequently, they would operate at full capacity without needing to hire new employees. Furthermore, larger companies have the resources and the opportunities to train their staff, whereas smaller companies might not. For example, Duetsch and Struck (2014) show that more possibilities for development are one reason for greater job stability at larger firms.

In a study of the impact of a firm's reputation on labor productivity, Stuebs and Sun (2010) find that more reputable firms are associated with higher labor efficiency. They argue that firms with a better reputation have a larger labor supply. Therefore, these firms have their pick of the best employees. Additionally, employees are more motivated by their firm's reputation. We think that they are also more pressured due to the large supply of labor. Size and reputation are not necessarily the same, nevertheless, we think that in the insurance industry size could be indicative of reputation and brand. This leads to our second hypothesis.

Hypothesis 2: *Larger insurers use less labor.*

Diversification of business lines – In the insurance literature, there are two lines of thought on the impact of business diversification on efficiency. The strategic focus hypothesis claims that insurers who concentrate on their core business are more efficient. In terms of labor utilization, specialized insurers can train and educate their employees

to perform specific tasks. They also may have fewer business processes and can optimize and standardize them more easily. Thus, specialized insurers and their employees become more efficient because they do similar tasks repetitively.

In contrast, the conglomeration hypothesis postulates that insurers operating in more business lines should profit from the effects of synergy and are therefore more efficient. For example, they may need only one team for risk management, actuarial service, and human resources. Therefore, because they can share many of their resources, they may more readily operate at full capacity and have a more diversified business. Additionally, diversified insurers may have better brand recognition and, like large insurers, have access to more motivated employees.

The empirical evidence in the efficiency literature is quite mixed. For example, Luhnen (2009) shows that specialization in the German property and casualty insurance market (i.e., the strategic focus hypothesis) creates higher efficiency values. In contrast, Biener et al. (2016) show that Swiss property and casualty insurance conglomerates are more efficient. Other studies analyze the efficiency between specialized insurance groups (only p/c or life insurance) and diversified insurance groups (offering p/c and life insurance). Their results are not consistent. For example, according to Cummins, Weiss, Xie and Zi (2010) the strategic focus is superior. In contrast, Mahlberg and Url (2003) find a positive relation between diversified insurance groups and cost efficiency. However, as we use diversification in p/c business lines, their results cannot be directly applied to our setting. Given our focus on the German market, we follow Luhnen's (2009) results and formulate the following hypothesis:

Hypothesis 3: *Specialized insurers use labor more efficiently.*

Premium growth – Insurers that want to strategically grow, must invest heavily in, for instance, marketing campaigns and new office equipment. Cummins and Nini (2002) hypothesize that insurers that want to grow must save up capital so that they do not have to raise it later. This argument may not apply to labor (i.e., insurers are not hiring employees before they start growing). Insurers may not conserve their labor force for later purposes; labor is an expensive resource. Insurers would first use the staff that they have while operating at full capacity. Thus, it seems reasonable to assume that insurers start hiring when they have an open position. But when they are already operating at full capacity or if they want to grow more aggressively, they need to hire more employees. This could lead to an inefficient use of labor, as new employees must be oriented and trained. More experienced employees might have to assist the new hires. Luhnen (2009) shows that German p/c insurers with higher growth rates are less cost efficient, which would be in line with our second reason. Based on our thoughts, we are ambivalent about this relationship. However, following Luhnen's (2009) results, we investigate:

Hypothesis 4: *Insurers with higher premium growth rates over-utilize labor more.*

Distribution – Another important aspect of labor utilization is the choice of distribution channel. We analyze the difference between insurers with agencies (independent or exclusive) and those without—direct insurers—which make their sales usually via phone, internet or mail. In terms of operating expenses, direct insurers have lower costs as they, for example, save money on local branches with sales staff. Moreover, they profit from centralization of jobs. Additionally, as not all products can be easily sold via a direct distribution channel, their product portfolio and service may be less complex. Many studies compare direct writers (direct and exclusive agent insurers) with independent agent insurers and almost all of them find cost advantages for direct writers (e.g., Berger, Cummins, & Weiss, 1997; Luhnén, 2009). However, our data set does not allow us to divide direct writers into direct insurers and exclusive agent insurers as we have an identifier only for direct insurers. Therefore, we only compare direct insurers with agent (exclusive and independent) insurers. Due to the less complex business, we think that direct insurers do not need a lot of labor and furthermore, they can centralize jobs more efficiently. Thus, we hypothesize:

Hypothesis 5: *Agent insurers use more labor than direct insurers.*

Regional factor – In line with the reputation hypothesis, we argue that insurers in regions with better quality of life (i.e., higher life expectancy, better education and higher income) have more productive labor. One reason could be that employers should have a larger labor supply in regions with better life quality. Thus, they can choose from among the most productive candidates. Moreover, employees may be more productive as they are pressured by the larger supply. Furthermore, investigating particular components of life quality, Craig, Pardey, and Roseboom (1997) find in a cross-country study that labor productivity is higher in countries with higher life expectancy, and, for example, Choudhry (2009) reveals a positive relationship between education and labor productivity. Thus, in summary, we hypothesize:

Hypothesis 6: *Insurers in regions with higher life quality use less labor.*

4 Sample data and methodology

4.1 Data sources

We consider the German p/c insurance industry (excluding health insurers), for which we have firm-specific historical data from annual reports for 1956 through 2015. We obtain the annual firm-level data from publications of the *Hoppenstedt Versicherungsjahrbuch* (Luhnén, 2009; Mahlberg & Url, 2010; Braun, Schmeiser, & Rymaszewski, 2015), which include all relevant firm information (i.e., financial data, organizational and distribution form). We manually collected the data from 1956–2010

from the physical books and the data from 2011–2015 from digital copies.

For the data envelopment analysis (DEA), we only include insurers with positive total and invested assets, equity, technical reserves, employees, losses and premium income. We collect input prices from several sources. We obtain price indices information from *Deutsche Bundesbank* and the compensation data from the German national account published by the Federal Statistical Office (Destatis).⁷² All monetary values are deflated to 2015 values and the values before year 2000 are converted into EUR values.

The final (unbalanced) sample for the DEA analysis consists of 298 p/c insurers with data on 9,394 firm years. Over the entire period, the sample is highly representative of the German p/c insurance market covering on average approximately 90 percent of total premiums written. Moreover, our data for the long time period 1956–2015 exhibits less heterogeneity than the datasets considered so far. However, as we use the standard deviation of the ROE over the past three years as one independent variable in our regression analysis, the sample size in our regression reduces to 288 p/c insurers and 8,257 firm years. We report the sample size separately in each table of results.

4.2 DEA methodology

In an ideal situation, we would know the production function of an insurance company (i.e., how much of inputs it should use to produce a given amount of output). But as the production functions are naturally unknown, we determine each year the efficiency frontier from p/c insurers in our sample.

A fully efficient firm is defined as the best practice or benchmark firm (Farrell, 1957). This means that no other firm uses less input to produce the same amount of output (input orientation) or produces more output with the same the input (output orientation). All best practice firms in the sample built the efficient frontier per year. Every firm on the efficiency (benchmark) frontier has an efficiency score of 1, meaning that they are 100 percent efficient. Every other firm in the sample (not operating on the efficient frontier) is compared to a linear combination of efficient firms. Depending on their use of inputs, they have an efficiency score between 0 and 1.⁷³

We use cost efficiency to determine the optimal input mix for each insurer. Cost efficiency is the product of technical and allocative efficiency. A firm is said to be technically efficient if it minimizes the input conditional on the output (Cummins &

⁷² For the time period 2000–2017 this data is directly available. For 1991–2000 we use the compensation growth rates from a different sector including the financial service industry per federal state and apply them to the given compensation values from the year 2000. Prior the year 1991, we do not have compensation data per federal state, thus we apply the German compensation growth rates of this sector until 1970 and the consumer price index until 1956.

Weiss, 2013). Every firm on the efficient frontier fulfills this condition. However, if we limit ourselves to technical efficiency, there is, for most insurers, still room for improvement because the technical efficiency values do not consider the optimal allocation of inputs. Only cost-efficient firms are technically and allocatively efficient. Therefore, we determine for each insurer an optimal cost-efficient insurer (i.e., a linear combination of cost-efficient insurers) and compare the inputs of both insurers.

We use the non-parametric mathematical programming approach (i.e., DEA), suggested by Charnes, Cooper, and Rhodes (1978) to determine the efficient frontier and the cost-efficient insurer. The optimal input mix I^{s*} for a cost inefficient insurer s ($s = 1, 2, \dots, S$), which uses M inputs to produce N outputs, is given by the solution x ($M \times 1$ vector) of the following linear problem (assuming variable return to scale):

$$(8) \quad \min_{x, \lambda^s} (p^s)^T x, \text{ subject to } O\lambda^s \geq O^s, x \geq I\lambda^s, \lambda^s \geq 0, 1^T \lambda^s = 1,$$

where p^s is an $M \times 1$ input price vector of insurer s , I is an $M \times S$ input matrix used by all insurer in the sample, O is an $N \times S$ matrix of all outputs produced by all insurer and O^s is the $N \times 1$ output vector for insurer s . The vector λ^s is an $S \times 1$ intensity vector for insurer s used to construct the optimal insurer s^* as a convex combination of cost-efficient insurers. Let $pc^s = \sum_{i=1}^M p_i^s I_i^s$ be the total costs for producing the output O^s for insurer s , where $p_i^s > 0$ is the price and $I_i^s > 0$ is the amount of input i . The cost efficiency (CE) for insurer s is defined as:

$$(9) \quad CE^s = \frac{pc^{s*}}{pc^s}, \text{ with } p_i^s = p_i^{s*}.$$

4.2.1 Output

We apply the value-added approach, which is the standard method for measuring intangible insurance outputs (see e.g., Luhnén, 2009; Cummins & Weiss, 2013, Biener et al., 2016; Eling & Schaper, 2017). Insurance companies provide three services to the insured: 1) risk-pooling and -bearing; 2) financial services; and 3) financial intermediation. We use net losses (i.e., paid losses plus additions to reserves) as our proxy for the risk pooling and financial service function. We use the smoothing procedure from Cummins and Xie (2008) to correct for the “errors in variables” problem in the loss output. The intermediation output is represented by the total investment value.

4.2.2 Input and input prices

We follow the literature (e.g., Cummins & Weiss, 2013) and use equity and debt capital (i.e., technical reserves) as well as labor as our input variables. As most of the insurers in our sample are not publicly traded, we use book values and apply regression analysis to estimate the capital prices for each firm individually.

For the price of equity, we adapt the approach suggested by Cummins and Weiss (2013) and estimate an OLS-regression equation with realized ROE (ROE_t) as the dependent

variable. To do so, we first calculate the ROE based on book values and, as the DEA demands positive input prices, delete all negative values and truncate the values at the 99% percentile to exclude extreme values.⁷⁴ Second, we estimate the following OLS function:

$$(10) \quad ROE_t = \beta_0 + \beta_1 SIZE_t + \beta_2 LEV_t + \beta_3 DIV_t + \beta_4 ASM_t + \varepsilon_{i,t}^S,$$

whereas *SIZE* is the natural logarithm of total assets, *LEV* (leverage) is the ratio of technical reserves divided by total assets, *DIV* (diversification) is the Herfindahl index of written gross premiums per business line and *AM* (asset mix) is the Herfindahl index of the invested assets. For the regression results for refer to Table A.1 in Appendix A. Third, we use the estimated coefficients β_0 – β_4 to calculate the price of equity for each insurer in our sample by inserting the specific firm values into the regression function.⁷⁵

The price of debt capital is reflected in the premiums and dividend payments to policyholders (Cummins & Weiss, 2013). As suggested by Cummins and Weiss (2013), the price of debt capital can be calculated as total investment income minus the estimated income from equity capital divided by the total amount of debt capital. To smooth the debt price, we apply the regression procedure: 1) delete all values, which are negative and greater than the 99% percentile; 2) use realized price of debt capital as the independent variable in the regression model (10) above and estimate β_0 – β_4 ; and 3) use the estimated coefficients and calculate for each insurers the price of debt capital individually. We report the regression results in Table A.2 in Appendix A.

One key advantage of our data set is that we can obtain the number of employees directly from the *Hoppenstedt Versicherungsjahrbuch*.⁷⁶ As price of labor, we use the yearly

⁷⁴ We also check if truncating the values at 0 and the 95% percentile as well as the 5% and 95% percentile change our main results regarding the utilization of equity and labor. We do not find any significant changes of our results (see Appendix C).

⁷⁵ Recent studies (e.g., Cummins & Rubio-Misas, 2006; Biener et al., 2016) use a stock index, for example the MSCI World or a country specific index, to approximate the capital costs of equity. Cummins and Xi (2008) compare the efficiency scores when using size and risk adjusted capital costs with efficiency scores when assigning the same capital costs to every company. The authors obtain for both approaches similar results. In our case, we need variation in the cost of capital, as we analyze the capital utilization, thus we prefer to use the individual price of equity. In a robustness check (see Appendix C), we use the 10-year average returns of the German stock index (DAX) and monthly German money market rates – our utilization results do not change significantly.

⁷⁶ As we cannot fully ensure that the reported numbers are only used by the insurer itself or if it also uses employees from a holding company, we manually compare each reported number with an estimated number of employees. We estimate each insurers workforce with the ratio of operating and labor expenses, which is usually used as an approximation for the number of employees (e.g., Biener & Eling, 2011; Eling & Schaper, 2017). If the estimated number is about the same order of magnitude as the reported number, we use the reported number. If the numbers show large deviations, we compare both numbers with firm data from previous and later years and use the labor number, which seems to fit best in the historic trend. If an insurer only misses data for some years, but the size of operation is still comparable (i.e., premium volume has not

compensation per employee for the financial service industry, which includes the gross wage and social security contributions paid by the employer. To account for differences in regional wage levels, we use the compensation data of the federal state where the headquarters is located. Therefore, we assume that most employees work in the federal state of the headquarters. In Table 9, we present the summary statistics on the inputs, input prices, and outputs over the whole sample period.

Table 9. Summary statistics for inputs, input prices, and outputs
(1956–2015, 9,394 firm years, 2015 real values)

<i>Variable</i>	<i>Unit</i>	<i>Mean</i>	<i>St. Dev.</i>	<i>Min</i>	<i>Max</i>
Output					
Losses incurred	TEUR	122,204	327,785	1	5,575,496
Invested assets	TEUR	403,011	1,327,548	11	29,486,423
Input					
Equity capital	TEUR	84,208	223,031	71	3,162,651
Debt capital	TEUR	298,715	1,025,615	1	19,638,136
Labor	Quantity	678	1,829	1	26,731
Input prices					
Equity capital costs	%	9.7	2.2	1.5	14.8
Debt capital costs	%	6.1	1.1	2.2	10.6
Labor wages	EUR	61,276	9,200	44,439	91,257

4.3 Utilization analysis

To test our hypotheses, we first define the utilization for our inputs $i = \{labor, equity\}$ as follows:

$$(11) \quad U_{i,t}^s = \frac{I_{i,t}^s}{I_{i,t}^{s*}} - 1,$$

whereas $I_{i,t}^{s*}$ is the optimal amount of input i for insurer s ($s = 1, 2, \dots, S$) at time t and $I_{i,t}^s$ is the amount of input i the insurer is actually using. Therefore, if $U_{i,t}^s > 1$ insurer s over-utilizes input i , and if $U_{i,t}^s < 1$ insurer s under-utilizes it (Cummins & Nini, 2002).⁷⁷

In order to investigate the impact (significant or insignificant) and direction (positive or negative) of a firm factor on input utilization, we estimate for each input i the following year-fixed effects OLS regression model with the utilization ratio as our dependent variable and firm-specific values as independent variables:

$$(12) \quad U_{i,t}^s = \beta X_{i,t}^s + \gamma T_t + \varepsilon_{i,t}^s.$$

$X_{i,t}^s$ is the vector of firm characteristics. T_t is the year fixed effects vector, β and γ are the parameters to be estimated.

changed that much, total assets are in the same order of magnitude) to previous or later years, we use the reported numbers from previous or later years directly. We exclude all insurers, which do not report any employee information for at least one year in our dataset.

⁷⁷ It follows that the potential cost savings/investment per input $= (1 - \frac{1}{U_{i,t}^s}) \times I_{i,t}^s \times p_i^s$.

To test our hypotheses regarding the utilization of labor, we measure *size* (SIZE) by the natural logarithm of total assets, *business line diversification* (DIV) by the Herfindahl index of 15 business lines, *growth* (GRO) by the one-year gross premium growth rate, *distribution* (DIS) by a direct insurer dummy (only available since 1992), and *regional life quality* (HDI) by a dummy variable indicating if the Human Development Index⁷⁸ in the state of the insurer's headquarter is above the German average of the Human Development Index.

To analyze the findings from Cummins and Nini (2002) and to investigate the impact of firm factors on equity utilization, we add to our regression *use of reinsurance* (REI) measured by 1 minus the ratio of net to gross premiums, *asset risk* (AR) measured by the ratio of invested stock plus real estate to total investments, *income risk* (IR) measured by the three-year standard deviation of book-value return on equity⁷⁹, *ownership* (OWN) measured by a mutual dummy variable (equal to 1 if mutual, 0 if stock), and *longer tailed business* (LTB) measured by the ratio of loss reserves to incurred losses.⁸⁰ We also add these variables as controls in our labor utilization regression analysis.

Table 10 presents the summary statistics of the firm characteristics. We calculate the variance inflation factor and find no evidence for multicollinearity (all values < 2). Moreover, we find no severe correlation between our variables (see Appendix B Table B). We only find larger Pearson correlation coefficients (> 0.4; < -0.4) for the diversification and size variables, in other words, larger insurers tend to be more diversified.

⁷⁸ The Human Development Index combines life expectancy, education, and income level. It is available per state for the years 1990, 2000, 2010 and 2017. The German federal states, which are above the German average do not change over the time horizon, except for North Rhine-Westfalia (NRW), which Human Development Index is above average for 1990 and 2000. However, we do not count NRW as a federal state with above average life quality.

⁷⁹ Cummins and Nini (2002) also use the three-year standard deviation of ROE as a measure of asymmetric information. Insurers with a high volatile income have higher information asymmetries than insurers with a less volatile, i.e., less risky, business. In the rationale of Cummins and Nini (2002), insurers with higher asymmetric information (i.e., higher values of the three-year standard deviation of book-value return on equity) use less equity capital. However, this directly contradicts their income risk hypothesis, that insurer with higher income risk use more equity capital. They argue that the sign of this variable will indicate whether it measures asymmetric information or income risk. Cummins' and Nini's (2002) findings support the asymmetric information hypothesis.

⁸⁰ Because of data limitation, we cannot test two other hypotheses on geographical diversification and business type (commercial vs. retail).

Table 10. Summary statistics for firm characteristics
(1959–2015, 8,257 firm years)

<i>Variable</i>	<i>Mean</i>	<i>St. Dev.</i>	<i>Min</i>	<i>Max</i>
Variables for labor hypotheses				
Size (SIZ)	18.34	1.91	12.31	24.21
Business line diversification (DIV)	0.59	0.33	0.11	1.00
Premium growth (GRO)	0.07	0.20	-0.33	1.71
Distribution (DIS)	0.02	0.13	0.00	1.00
Regional life quality (HDI)	0.59	0.49	0.00	1.00
Additional variables for equity utilization				
Use of reinsurance (REI)	0.31	0.21	-0.01	0.87
Asset risk (AR)	0.47	0.23	0.00	1.00
Income risk (IR)	0.05	0.07	0.00	0.65
Mutual dummy (OWN)	0.33	0.47	0.00	1.00
Longer tailed business (LTB)	1.23	0.74	0.00	4.24

Note: Due to the calculation of the three-year standard deviation of book-value return on equity as a measure of the income risk (IR), the sample period is reduced to 1959–2015. To exclude extreme values, we winsorize the premium growth (GRO), the reinsurance use (REI), the ROE before the calculation of the standard deviation and the longer tailed business (LTB) to the 1% and 99% percentile. Our results regarding the utilization regressions are robust with respect to the choice of the percentiles. In Appendix C (see Tables C.5 and C.6) we present the results when winsorizing at the 5% and 95% percentile.

5 Empirical results

5.1 Efficiency levels and utilization of inputs.

In Figure 6 we present the average period pure technical efficiency (PTE), allocative efficiency (AE), and cost efficiency (CE) scores (assuming variable return to scale) for the total sample period of 1956–2015 and for 9,394 firm years. Over the whole sample, PTE is on average 0.81, ranging from 0.72 in 1972 to 0.88 in 2003. Our results are in line with Luhnén (2009), who reports an average PTE of 0.80 for the German p/c insurance industry for the sample period of 1995–2006, but they are slightly higher than those reported by Mahlberg and Url (2010), who arrived at an average PTE of 0.72 for German insurance groups between 1991–2006. The PTE values are also comparable to Hussels and Ward’s (2007) results of 0.76 for the German life insurance industry.

The cost efficiency (CE) values range from 0.48 in 1972 and 0.64 in 2006, with an average of 0.55 over the entire sample period. Our results are slightly higher than those of Luhnén (2009), who identifies an average CE score of 0.48. They are considerably higher than the average CE score of 0.40 reported by Mahlberg and Url (2010). For the German life insurance industry, Hussels and Ward (2007) and Trigo-Gamarra and Growitsch (2010) find an average CE score of 0.56 and 0.48 for the time period of 1991–2002 and 1997–2005, respectively.

For the duration of our sample period the PTE values are quite high, implying that the German p/c insurers adapt to the state-of-the-art technology. However, some insurers always seem to use the technology more efficiently; it seems impossible to close that gap. The PTE scores have slightly increased since the mid-1970s. This may be attributed

to the increased use of computers, which offer every company the same possibilities and access to the start-of-the-art technology. Before that, insurers employing the most skilled experts (being a limited resource) may have had a competitive advantage.

The main driver for the low CE values is the allocative inefficiency; in other words, insurers do not choose the best (cost-minimizing) input combination. Based on the CE results, we report in Figure 7 the utilization of labor and equity per year over the entire sample period. Insurers use too much labor input, with an average of 83 percent, which fluctuates between 58 percent and 132 percent, but it seems that there is no general trend in the utilization of labor. The average utilization of equity is around 7 percent and falls between -29 percent and 54 percent. German p/c insurers have used too less equity capital in the 1960s and 1980s, thus, cost efficient insurers have used more equity and less labor in these periods. Moreover, we observe an increase of the equity over-utilization in the mid-1990s. This may be explained by the deregulation in 1994. Until then, German p/c insurers' prices and products had been strictly regulated.⁸¹ As a result, the German p/c insurance sector had no need for profound efficiency improvements as the competitive pressure was limited.⁸² Maybe under the new competitive pressure, some insurers started to optimize (minimize) their use of equity capital. If this was true, the overall efficiency should have decreased. Therefore, we think some insurers may have increased their equity to show solvency or to grow their business (in line with the premium growth hypothesis, see Cummins & Nini, 2002). However, the additional capital has not severely influenced their efficiency.

When analyzing the drivers of cost efficiency, we find that the cost inefficiency (1-CE, the cost saving potential) is mainly driven by the inefficient use of labor over the entire sample period (Figure 8), whereas the inefficient use of equity is slightly increasing.

In summary, we confirm our first hypothesis that the labor input offers a high potential for improvement. We do not observe that the utilization of labor increases over the past years. Instead, we find rising equity levels, which so far have no large impact on insurers' efficiency. One possible explanation could be that German p/c insurers increased the equity (i.e., investments) to grow into new markets.

⁸¹ The European insurance industry has been deregulated by the third generation of insurance directives in 1994. Before that prices, products, and operations were highly regulated in Germany (Hussel & Ward, 2007). Furthermore, the new directive allowed insurers to operate with one license in the whole European Economic Area (Mahlberg & Url, 2010).

⁸² Leibenstein (1966) argues that competition increases the motivation of staff and firms to be more efficient. In situation with lighter competition, they prefer not to put all their efforts and resources into efficiency maximization.

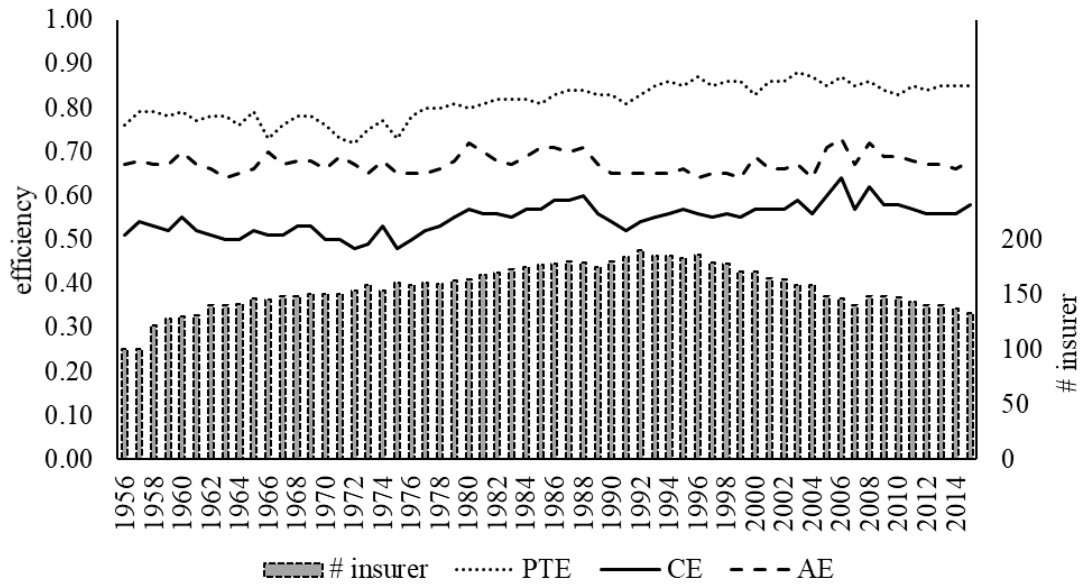


Figure 6. Development of DEA efficiency scores over time.



Figure 7. Development of equity and labor over-/ under-utilization over time.

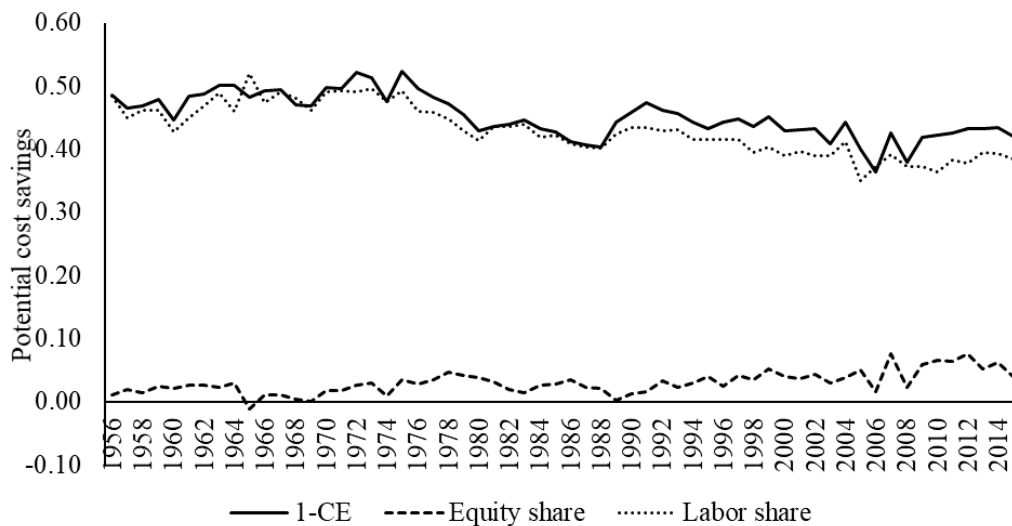


Figure 8. Potential cost savings per input.

5.2 Labor utilization

We report the regression results for labor utilization in Table 11 and the development over time in Table 12. Most of our hypotheses are confirmed by our regression results.

Size – In line with studies from the manufacturing industry (e.g., van Ark & Monnikhof, 1996; Leung et al., 2008) and research on insurance efficiency (e.g., Cummins & Zi, 1998; Cummins & Rubio-Misas, 2006; Eling & Luhnen, 2010), we expect a negative relation between firm size and labor utilization. The regression results confirm our hypothesis 2 as shown in Table 11 and they are consistent over time (Table 12). For the years 2010 through 2015 we cannot confirm this inverse relationship. However, the growth variable seems to explain most of the labor utilization, which might offset the influence of size.

Diversification of business lines – Hypothesis 3, that specialized insurers use less labor, is confirmed by our analysis (Table 11). As we have shown, labor is the driver of cost inefficiency, thus, we can confirm Luhnen's (2009) results showing that specialized German p/c insurers are more efficient. Our results contradict the conglomeration theory (Biener et al., 2016), that diversified insurers can profit from synergy effects along their value chain. The results are consistent over time (Table 12), but not for 2010–2015.

Premium growth – We can confirm that insurers with higher growth rates use too much labor (hypothesis 4). The results are in line with Luhnen (2009), who emphasizes that insurers with higher growth rates are less cost efficient. Our belief that growing insurers use first their existing employees is only confirmed for the years 1980–1989 (Table 12).

Distribution – As direct insurers should have fewer complex products and service offerings, we expect direct insurers to use less labor. However, we cannot confirm hypothesis 5 (Table 11). Our results are not in line with Luhnen (2009), whose results show that direct insurers are more cost efficient than agent insurers. However, our results seem to be strongly influenced by the time period 1990–1999, as we find a non-significant relationship for the periods after 2000 (Table 12). The results might be explained by the transformation from agent insurers to direct insurers in the middle of the 1990s. Thus, the first direct insurers may have still used the whole infrastructure of agent insurers. Only later new direct insurers entered the market building infrastructure from scratch and thus have been able to use labor more efficiently. Due to data constraints, we cannot report results prior to 1990–1999.⁸³

⁸³ In Appendix D we compare cost efficiency values between direct and non-direct insurers. The analysis confirms that there are only efficiency differences between insurers with different distribution channels in the 1990s. The results become less significant if we use the estimated labor numbers (ratio of operating and labor expenses) to increase the number of direct insurers as sometimes labor book values are not given for direct

Regional factor – We argue that insurers in states with a better quality of life (measured by the Human Development Index) should have it easier to find the best employees, because the labor supply will be higher there. Another effect could be that employees in regions with a better quality of life are more productive and motivated as they are more afraid of being replaced (which is easier for insurers because of the higher labor supply). Our results confirm our assumption (Table 11).

With respect to our control variables, we find that insurers with more reinsurance use, mutuals, and insurers with higher income risk significantly use too much labor. Insurers with longer tailed business significantly use too less labor. These results are rather exploratory as we had no prior assumption regarding their impact on labor utilization.

Table 11. Regression results for labor utilization

<i>Variable</i>	<i>Expected sign</i>	<i>Coefficients</i>
Main variables		
Intercept		20.917*** (1.784)
Size (SIZ)	–	-1.108*** (0.074)
Business line diversification (DIV)	–	-1.821*** (0.385)
Premium growth (GRO)	+	1.959*** (0.558)
Distribution (DIS)	–	2.239*** (0.863)
Regional life quality (HDI)	–	-0.646*** (0.222)
Control variables		
Use of reinsurance (REI)		6.767*** (0.571)
Asset risk (AR)		-0.656 (0.605)
Income risk (IR)		3.706** (1.629)
Mutual dummy (OWN)		1.082*** (0.240)
Longer tailed business (LTB)		-1.125*** (0.162)
Year fixed effects		YES
Sample size		8,257
Adjusted R ²		0.145

Note: ***, **, and * represent significance at the 1 percent, 5 percent and 10 percent levels, respectively. As the dependent variable we use the ratio of actual-to-optimal labor minus one.

insurers. Additionally, we analyzed the meta- and cross-efficient-frontiers (e.g., Cummins, Weiss, & Zi, 1999). However, the results are not meaningful due to the small sample size of direct insurers.

Table 12. Regression results for labor utilization over time

<i>Variable</i>	<i>1959–2015</i>	<i>1959–1969</i>	<i>1970–1979</i>	<i>1980–1989</i>	<i>1990–1999</i>	<i>2000–2009</i>	<i>2010–2015</i>
Main Variables							
Intercept	20.917*** (1.784)	12.229*** (1.190)	19.243*** (1.158)	22.051*** (1.891)	34.050*** (3.359)	26.965*** (4.146)	10.612 (11.480)
SIZ	-1.108*** (0.074)	-0.662*** (0.058)	-0.720*** (0.055)	-1.014*** (0.087)	-1.849*** (0.157)	-1.054*** (0.203)	0.165 (0.571)
DIV	-1.821*** (0.385)	-0.524* (0.299)	-2.382*** (0.302)	-2.578*** (0.467)	-0.823 (0.827)	-1.931** (0.967)	1.085 (2.533)
GRO	1.959*** (0.558)	1.920*** (0.368)	-0.647 (0.418)	-1.410** (0.701)	4.745*** (1.109)	-0.507 (1.388)	14.580** (6.959)
DIS	2.239*** (0.863)				6.382*** (1.913)	0.842 (1.330)	1.212 (3.703)
HDI	-0.646*** (0.222)	-0.118 (0.149)	-0.710*** (0.168)	-0.228 (0.261)	0.245 (0.501)	-0.980* (0.575)	-3.246* (1.675)
Control							
REI	6.767*** (0.571)	1.854*** (0.410)	3.081*** (0.438)	3.938*** (0.687)	8.657*** (1.298)	12.079*** (1.563)	11.747** (4.653)
AR	-0.656 (0.605)	1.987*** (0.415)	-1.332*** (0.452)	-0.304 (0.795)	5.198*** (1.452)	0.589 (1.577)	-14.494*** (3.960)
IR	3.706** (1.629)	4.271*** (1.638)	4.435*** (1.316)	2.920 (2.129)	8.668** (3.544)	6.254* (3.301)	-21.639* (12.033)
OWN	1.082*** (0.240)	-0.474*** (0.173)	-0.531*** (0.179)	0.192 (0.283)	1.770*** (0.564)	0.327 (0.692)	6.355*** (1.908)
LTB	-1.125*** (0.162)	-0.316** (0.136)	-1.262*** (0.141)	-0.576*** (0.211)	-0.084 (0.345)	-1.603*** (0.373)	-1.941* (1.102)
Year FE	YES	YES	YES	YES	YES	YES	YES
Sample size	8,257	1,358	1,422	1,598	1,674	1,429	776
Adj. R ²	0.145	0.185	0.254	0.167	0.194	0.149	0.066

Note: ***, **, and * represent significance at the 1 percent, 5 percent and 10 percent levels, respectively. As the dependent variable we use the ratio of actual-to-optimal labor minus one.

5.3 Equity utilization

In this section, we briefly analyze the hypotheses by Cummins and Nini (2002). We present our results on the impact of the firm characteristics on equity utilization in Table 13. In line with Cummins and Nini's (2002) hypotheses, we can confirm a negative relationship for firm size and long tailed business. However, the relation between size and equity utilization has inverted in later periods (Table 14). This may be explained by the introduction of Solvency I and II, which may have led insurers to accumulate capital. Larger insurers may have an easier access to the capital market and could raise more capital to signal stronger solvency. We confirm their findings with respect to income risk. Thus, the income risk variable seems to capture the asymmetric information between managers and investors (Cummins & Nini, 2002). We find a significant positive relationship for asset risk. Moreover, we can confirm Cummins and Nini's (2002) hypotheses for diversification (diversified insurers use less equity capital) and premium growth – neither hypothesis could be confirmed by Cummins and Nini (2002).

Over the entire sample period, we cannot confirm that mutual insurers use less equity capital; all we find is a significant negative relationship for the period 1959–1969 (Table

14). In all other periods, mutual insurers use more equity capital than stock insurers. Our results are in line with the finding that mutual insurers may have limited access to the capital market and therefore save up capital. Moreover, our findings contradict that owners of mutual insurers try to mitigate the moral hazard of insurance managers (to resolve the owner–manager conflict) by decreasing the amount of equity. In contrast to Cummins and Nini (2002), our measure of reinsurance use is positively correlated with the use of equity. This can be explained by the fact that we use net values in our analysis.⁸⁴

Table 13. Regression results for equity utilization

<i>Variable</i>	<i>Expected results Cummins and Nini (2002)</i>	<i>Coefficients</i>
Intercept		0.352** (0.146)
Size (SIZ)	–	-0.016*** (0.006)
Business line diversification (DIV)	+	0.279*** (0.031)
Premium growth (GRO)	+	0.259*** (0.046)
Reinsurance use (REI)	–	0.951*** (0.047)
Asset risk (AR)	+	0.165*** (0.049)
Income risk (IR)	ambiguous	-0.989*** (0.133)
Mutual dummy (OWN)	ambiguous	0.017 (0.019)
Longer tailed business (LTB)	–	-0.092*** (0.013)
Year fixed effects		YES
Sample size		8,257
Adjusted R ²		0.116

Note: ***, **, and * represent significance at the 1 percent, 5 percent and 10 percent levels, respectively. As the dependent variable we use the ratio of actual-to-optimal equity minus one.

⁸⁴ For example, let us consider two insurers A and B with the same net invested assets. Both insurers have the same gross technical reserves, but insurer B uses more reinsurance. In consequence, the net reserves of insurer B are lower. Using net balance sheet data, we know that approximately: $\text{equity}_A + \text{net reserves}_A = \text{equity}_B + \text{net reserves}_B$. As $\text{net reserves}_B < \text{net reserves}_A$, it follows that $\text{equity}_A > \text{equity}_B$.

Table 14. Regression results for equity utilization over time

<i>Variable</i>	<i>1959–2015</i>	<i>1959–1969</i>	<i>1970–1979</i>	<i>1980–1989</i>	<i>1990–1999</i>	<i>2000–2009</i>	<i>2010–2015</i>
Main Variables							
Intercept	0.352** (0.146)	2.293*** (0.402)	0.292 (0.280)	1.704*** (0.268)	-0.412 (0.258)	-0.713*** (0.263)	-1.909*** (0.422)
SIZ	-0.016*** (0.006)	-0.143*** (0.020)	-0.032** (0.013)	-0.074*** (0.012)	0.014 (0.012)	0.051*** (0.013)	0.129*** (0.021)
DIV	0.279*** (0.031)	0.644*** (0.101)	0.278*** (0.072)	0.214*** (0.066)	0.245*** (0.063)	0.083 (0.061)	0.149 (0.093)
GRO	0.259*** (0.046)	0.694*** (0.125)	0.223** (0.101)	0.317*** (0.099)	0.136 (0.084)	-0.044 (0.088)	0.615** (0.256)
REI	0.951*** (0.047)	1.877*** (0.139)	0.827*** (0.106)	0.983*** (0.097)	0.802*** (0.100)	0.514*** (0.099)	0.189 (0.171)
AR	0.165*** (0.049)	-0.046 (0.141)	0.195* (0.109)	0.000 (0.112)	0.090 (0.112)	0.103 (0.099)	0.100 (0.144)
IR	-0.989*** (0.133)	-1.739*** (0.556)	-0.308 (0.319)	-0.488 (0.301)	0.280 (0.272)	-1.138*** (0.209)	-1.724*** (0.438)
OWN	0.017 (0.019)	-0.331*** (0.058)	0.004 (0.043)	0.100** (0.040)	0.067 (0.042)	0.136*** (0.043)	0.530*** (0.068)
LTB	-0.092*** (0.013)	-0.182*** (0.046)	-0.124*** (0.034)	-0.143*** (0.030)	-0.153*** (0.026)	-0.105*** (0.024)	-0.132*** (0.040)
Year FE	YES	YES	YES	YES	YES	YES	YES
Sample size	8,257	1,358	1,422	1,598	1,674	1,429	776
Adj. R ²	0.116	0.347	0.113	0.178	0.072	0.111	0.143

Note: ***, **, and * represent significance at the 1 percent, 5 percent and 10 percent levels, respectively. As the dependent variable we use the ratio of actual-to-optimal equity minus one.

6 Conclusion

Scholars have investigated the productivity and efficiency of the insurance industry, but only Cummins and Nini (2002) have analyzed the utilization of input factors and firm characteristics driving the usage of equity.

In this paper we quantify the productivity and efficiency in the German p/c insurance industry from 1956 to 2015. We use DEA analysis to study the utilization of the inputs labor and equity and use OLS regression to understand which firm characteristics influence labor and capital utilization. The average pure technical efficiency is 0.81 for our entire sample period. But our average cost efficiency value of 0.55 is much lower. The cost inefficiency is driven by the fact that German p/c insurers are not choosing the cost-minimizing input combination. Based on these results, we find that the labor input is the main driver of cost inefficiency and offers the most room for improvement. We observe that in recent years the inefficiency resulting from the labor input has decreased and that capital levels have increased, which could become another and new source of inefficiency.

In our analysis of firm characteristics driving the utilization of labor, we find support that larger insurers use less labor. We find evidence that more specialized insurers use labor more efficiently. Regarding premium growth, we find that insurers, that want to grow, use more labor. Thus, we additionally show that insurers that grow not only invest in costly marketing campaigns, which increases the operating costs (Luhnen, 2009), but

also invest in new employees. We do not find support for our hypothesis that direct insurers use less labor. The results may be driven by former non-direct insurers which have become direct insurers. Therefore, they still use the whole prior labor force. These results may change with more new direct insurers entering the market. They can build their infrastructure from scratch and therefore use the labor input with the right volume. Insurers in regions with better quality of life are found to use less labor. We hypothesized that quality of life could be an indicator for a larger labor supply as more people want to live in those regions. As a result, insurers in those regions can hire the most productive employees. Therefore, they can use less labor.

We confirm most of the hypotheses from Cummins and Nini (2002) with respect to firm factors influencing the utilization of equity. We find support for the financial distress hypothesis in the size, diversification and asset risk variables. Contrary to Cummins and Nini (2002) we find that German mutual p/c insurers use more equity capital compared to stock insurers. We interpret this finding that mutual insurers pile up equity capital as they have limited access to the capital market. Thus, the present owner–manager conflict at mutual insurers is not resolved by decreasing equity capital. In line with Cummins and Nini (2002), we find that insurers with longer tailed business and higher information asymmetries use less equity capital to resolve the manager–policyholders and manager–investor conflict, respectively. Furthermore, our results show that growing insurers stack up capital that they do not have to raise expensive capital later. Our results complement the work from Cummins and Nini (2002) as we focus on the utilization of labor, which is the largest component of cost inefficiency.

The findings have implications for insurance managers and policymakers. Our results show that there is a large potential in the insurance industry to reduce the amount of labor to become more efficient. But, due to the strong German labor laws, unions as well as work councils reducing the workforce is complicated for insurers and often only undertaken by retirement. If technology takes over more and more tasks, the utilization of labor may increase in companies that cannot flexibly reduce its workforce. In contrary, new competitors that can use technology from the beginning can optimize their utilization of labor and therefore have a competitive advantage. Moreover, as German p/c insurers do not only operate in Germany, they may have a competitive disadvantage compared to insurers in countries, in which technology is used more often while having more liberal labor laws. In addition, policymakers must find a solution how to deal with all those employees that may get replaced by technology. We think that this development will have a large impact on the cohesion of society and that ideas of societal involvement must be developed.

Our analysis shows potential for future research in various directions. For example, the impact of the utilization on revenue and profit efficiency could be further analyzed.

Moreover, it could be valuable to distinguish between new direct insurers and transformed direct insurers. So far, the sample size of new direct insurers is still limited. Future data may make the analysis more robust. Furthermore, meta- and cross-frontier analysis could help to understand if non-direct and direct insurers use the same technology or if they should be analyzed separately. Additionally, it would be very helpful to distinguish between various job positions to further analyze each positions' utilization. Based on that one could make more detailed predictions on the future of labor in the insurance industry. Additionally, numbers on insurers' spending into technology could be helpful to see if these insurers improved their productivity and efficiency due to technological investments.

Moreover, it could be interesting to analyze the utilization of the life insurance industry and to compare our results within a European context. For example, it could be insightful if insurers in countries with more liberal labor laws (e.g., Switzerland or U.K.) use less labor and if this leads to a competitive advantage in terms of productivity and efficiency. Furthermore, it could be interesting to compare our results with the banking sector and the manufacturing industry to see how labor and capital are used. With future data the impact of recent technological developments on insurers efficiency could be analyzed in more detail.

References

- Berger, A. N., Cummins, J. D., & Weiss, M. A. (1997). The coexistence of multiple distribution systems for financial services: the case of property-liability insurance. *Journal of Business*, 70(4), 515–546.
- Biener, C., & Eling, M. (2011). The performance of microinsurance programs: a data envelopment analysis. *Journal of Risk and Insurance*, 78(1), 83–115.
- Biener, C., Eling, M., & Wirfs, J. H. (2016). The determinants of efficiency and productivity in the Swiss insurance industry. *European Journal of Operational Research*, 248(2), 703–714.
- Braun, A., Schmeiser, H., & Rymaszewski, P. (2015). Stock vs. mutual insurers: who should and who does charge more? *European Journal of Operational Research*, 242(3), 875–889.
- Charnes, A., Cooper, W. W., & Rhodes, E. (1978). Measuring the efficiency of decision making units. *European Journal of Operational Research*, 2(6), 429–444.
- Choudhry, M. T. (2009). Determinants of labor productivity: an empirical investigation of productivity divergence. Working Paper.
- Craig, B. J., Pardey, P. G., & Roseboom, J. (1997). International productivity patterns: accounting for input quality, infrastructure, and research. *American Journal of Agricultural Economics*, 79(4), 1064–1076.
- Cummins, J. D., & Nini, G. P. (2002). Optimal capital utilization by financial firms: evidence from the property-liability insurance industry. *Journal of Financial Services Research*, 21(1–2), 15–53.
- Cummins, J. D., & Rubio-Misas, M. (2006). Deregulation, consolidation, and efficiency: evidence from the Spanish insurance industry. *Journal of Money, Credit and Banking*, 38(2), 323–355.
- Cummins, J. D., Rubio-Misas, M., & Zi, H. (2004). The effect of organizational structure on efficiency: evidence from the Spanish insurance industry. *Journal of Banking and Finance*, 28(12), 3113–3150.
- Cummins, J. D., & Weiss, M. A. (2013). Analyzing firm performance in the insurance industry using frontier efficiency and productivity methods. *Handbook of insurance* (pp. 795–861). New York: Springer.
- Cummins, J. D., Weiss, M. A., Xie, X., & Zi, H. (2010). Economies of scope in financial services: a DEA efficiency analysis of the US insurance industry. *Journal of Banking and Finance*, 34(7), 1525–1539.
- Cummins, J. D., Weiss, M. A., & Zi, H. (1999). Organizational form and efficiency: the coexistence of stock and mutual property-liability insurers. *Management Science*, 45(9), 1254–1269.
- Cummins, J. D., & Xie, X. (2008). Mergers and acquisitions in the US property-liability insurance industry: productivity and efficiency effects. *Journal of Banking and Finance*, 32(1), 30–55.

- Cummins, J. D., & Zi, H. (1998). Comparison of frontier efficiency methods: an application to the US life insurance industry. *Journal of Productivity Analysis*, 10(2), 131–152.
- Deloitte (2018). The future of talent in insurance. Retrieved from https://www2.deloitte.com/content/dam/Deloitte/ie/Documents/FinancialServices/IE_FS_talentinInsurance_0918_FINAL3.pdf, accessed on 31 March 2020.
- Duetsch, M., & Struck, O. (2014). Atypical employment and the risks for preservation of occupational skills. *German Journal of Industrial Relations*, 21(1), 58–77.
- Eling, M., & Lehmann, M. (2018). The impact of digitalization on the insurance value chain and the insurability of risks. *Geneva Papers on Risk and Insurance – Issues and Practice*, 43(3), 359–396.
- Eling, M., & Luhnen, M. (2010). Efficiency in the international insurance industry: A cross-country comparison. *Journal of Banking and Finance*, 34(7), 1497–1509.
- Eling, M., & Schaper, P. (2017). Under pressure: how the business environment affects productivity and efficiency of European life insurance companies. *European Journal of Operational Research*, 258(3), 1082–1094.
- Eling, M., Schmeiser, H., & Schmit, J. T. (2007). The Solvency II process: overview and critical analysis. *Risk Management and Insurance Review*, 10(1), 69–85.
- Farrell, M. J. (1957). The measurement of productive efficiency. *Journal of the Royal Statistical Society*, 120(3), 253–281.
- Hussels, S., & Ward, D. R. (2007). The impact of deregulation on the German and UK life insurance markets: an analysis of efficiency and productivity between 1991 and 2002. Working Paper, SOM Research Paper Series 4/07, Cranfield University.
- Johansson, S., & Vogelgesang, U. (2015). Insurance on the threshold of digitization: implications for the life and p&c workforce. McKinsey & Company. Retrieved from <http://www.mckinsey.com/industries/financial-services/our-insights/insurance-on-the-threshold-of-digitization>, accessed on 31 March 2020.
- Leibenstein, H. (1966). Allocative efficiency vs. “X-efficiency”. *American Economic Review*, 56(3), 392–415.
- Leung, D., Meh, C., & Terajima, Y. (2008). Firm size and productivity. Staff Working Papers 08–45, Bank of Canada.
- Luhnen, M. (2009). Determinants of efficiency and productivity in German property-liability insurance: evidence for 1995–2006. *Geneva Papers on Risk and Insurance – Issues and Practice*, 34(3), 483–505.
- Mahlberg, B., & Url, T. (2003). Effects of the single market on the Austrian insurance industry. *Empirical Economics*, 28, 813–838.
- Mahlberg, B., & Url, T. (2010). Single market effects on productivity in the German insurance industry. *Journal of Banking and Finance*, 34(7), 1540–1548.

- Malhotra, R. (2015). The insurance workforce of the future: why will so many insurers fail to achieve their digital potential? Accenture strategy. Retrieved from https://www.accenture.com/t00010101t000000__w_/it-it/_acnmedia/accenture/conversion-assets/dotcom/documents/global/pdf/dualpub_25/accenture-the-insurance-workforce-of-the-future.pdf, accessed on 31 March 2020.
- Staib, D., Puttaiah, M. H., & Tschekassin, O. (2019). World insurance: the great pivot east continues. Swiss Re sigma 3/2019. Retrieved from <https://www.swissre.com/institute/research/sigma-research/sigma-2019-03.html>, accessed on 31 March 2020.
- Stuebs, M., & Sun, L. (2010). Business reputation and labor efficiency, productivity, and cost. *Journal of Business Ethics*, 96, 265–283.
- Trigo-Gamarra, L., & Growitsch, C. (2010). Comparing single- and multichannel distribution strategies in the German life insurance market: an analysis of cost and profit efficiency. *Schmalenbach Business Review*, 62(4), 401–417.
- Van Ark, B., & Monnikhof, E. (1996). Size distribution of output and employment: a data set for manufacturing industries in five OECD countries, 1960s-1990. OECD Economics Department Working Papers No. 166.

Appendix A: Equity and debt capital costs regression results

Table A.1. Equity capital cost estimation OLS regression results (n=9,394)

<i>Variable</i>	<i>Realized book ROE</i>
SIZE – <i>logarithm of total assets</i>	0.006*** (0.001)
LEV – <i>technical reserves/total assets</i>	0.059*** (0.006)
DIV – <i>Herfindahl index of written gross premiums per business line</i>	0.014*** (0.003)
AM – <i>Herfindahl index of invested assets</i>	-0.046*** (0.008)
Constant	-0.035*** (0.013)

Note: ***, **, and * represent significance at the 1 percent, 5 percent and 10 percent levels, respectively. As the dependent variable we use realized ROE (net income/equity capital). We delete all negative capital prices and exclude extreme values above the 99% percentile. Standard errors are presented in parentheses.

Table A.2. Debt capital cost estimation OLS regression results (n=9,394)

<i>Variable</i>	<i>Realized price of debt capital</i>
SIZE – <i>logarithm of total assets</i>	0.005*** (0.000)
LEV – <i>technical reserves/total assets</i>	-0.064*** (0.002)
DIV – <i>Herfindahl index of written gross premiums per business line</i>	0.007*** (0.001)
AM – <i>Herfindahl index of invested assets</i>	-0.004 (0.003)
Constant	-0.008* (0.005)

Note: ***, **, and * represent significance at the 1 percent, 5 percent and 10 percent levels, respectively. As the dependent variable we calculate the realized debt capital price as suggested by Cummins and Weiss (2013) as follows: (total investment income - investment income due to equity)/debt capital. We delete all negative capital prices and exclude extreme values above the 99% percentile. Standard errors are presented in parentheses.

Appendix B: Correlation matrix

Table B. Pearson correlation and variance inflation factors (VIF) for regression regressors (1959–2015, 8,257 firm years)

<i>Variable</i>	SIZ	DIV	GRO	DIS	HDI	REI	AR	IR	OWN	LTB	VIF
SIZ	1.00	-0.44	-0.12	0.06	0.00	-0.20	-0.05	0.02	-0.09	0.38	1.72
DIV		1.00	0.06	0.00	0.09	-0.19	0.00	-0.01	0.00	-0.09	1.43
GRO			1.00	0.05	0.01	0.02	0.01	0.02	-0.06	-0.09	1.03
DIS				1.00	-0.02	-0.04	-0.16	0.06	-0.09	0.02	1.04
HDI					1.00	0.02	0.00	0.04	-0.18	0.00	1.05
REI						1.00	0.06	-0.03	-0.14	0.08	1.25
AR							1.00	-0.16	0.14	-0.09	1.08
IR								1.00	-0.06	0.06	1.03
OWN									1.00	-0.16	1.12
LTB										1.00	1.27

Appendix C: Robustness tests

Table C.1. Robustness tests OLS equity utilization depending on equity and debt capital prices

<i>Variable</i>	<i>Original: Truncate equity/debt costs at are 0 and 99% percentile</i>	<i>RT 1: Truncate equity/debt costs at are 0 and 95% percentile</i>	<i>RT 2: Truncate equity/debt costs at are 5% and 99% percentile</i>	<i>RT 3: use DAX 10- year avg. and monthly German money market rates</i>
Intercept	0.352** (0.146)	0.301** (0.145)	0.215 (0.139)	0.905*** (0.181)
SIZ	-0.016*** (0.006)	-0.016*** (0.006)	-0.009 (0.006)	-0.019** (0.008)
DIV	0.279*** (0.031)	0.280*** (0.031)	0.264*** (0.030)	0.350*** (0.039)
GRO	0.259*** (0.046)	0.285*** (0.045)	0.269*** (0.044)	0.330*** (0.057)
REI	0.951*** (0.047)	0.973*** (0.046)	0.914*** (0.045)	1.215*** (0.058)
AR	0.165*** (0.049)	0.193*** (0.049)	0.140*** (0.047)	0.053 (0.061)
IR	-0.989*** (0.133)	-1.026*** (0.132)	-1.003*** (0.127)	-1.766*** (0.165)
OWN	0.017 (0.019)	0.034* (0.019)	0.039** (0.018)	0.110*** (0.024)
LTB	-0.092*** (0.013)	-0.107*** (0.013)	-0.104*** (0.013)	-0.087*** (0.016)
Year FE	YES	YES	YES	YES
Sample size	8,257	8,257	8,257	8,257
Adj. R ²	0.116	0.124	0.120	0.202

Note: ***, **, and * represent significance at the 1 percent, 5 percent and 10 percent levels, respectively. As the dependent variable we use the ratio of actual-to-optimal equity minus one.

Table C.2. Robustness tests OLS labor utilization depending on equity and debt capital prices

<i>Variable</i>	<i>Original</i>	<i>RT 1</i>	<i>RT 2</i>	<i>RT 3</i>
Intercept	20.917*** (1.784)	21.355*** (1.798)	21.794*** (1.814)	21.079*** (1.501)
SIZ	-1.108*** (0.074)	-1.133*** (0.075)	-1.156*** (0.076)	-1.140*** (0.063)
DIV	-1.821*** (0.385)	-1.692*** (0.388)	-1.710*** (0.391)	-2.152*** (0.324)
GRO	1.959*** (0.558)	1.898*** (0.563)	1.809*** (0.568)	1.646*** (0.470)
DIS	2.239*** (0.863)	2.419*** (0.870)	2.627*** (0.878)	2.405*** (0.726)
HDI	-0.646*** (0.222)	-0.637*** (0.223)	-0.655*** (0.225)	-0.252 (0.186)
REI	6.767*** (0.571)	7.166*** (0.575)	7.305*** (0.580)	6.780*** (0.480)
AR	-0.656 (0.605)	-0.878 (0.610)	-0.924 (0.615)	0.511 (0.509)
IR	3.706** (1.629)	3.602** (1.642)	4.211** (1.656)	6.554*** (1.370)
OWN	1.082*** (0.240)	1.084*** (0.242)	1.090*** (0.244)	0.397** (0.202)
LTB	-1.125*** (0.162)	-1.203*** (0.163)	-1.229*** (0.165)	-1.497*** (0.136)
Year FE	YES	YES	YES	YES
Sample size	8,257	8,257	8,257	8,257
Adj. R ²	0.145	0.152	0.155	0.222

Note: ***, **, and * represent significance at the 1 percent, 5 percent and 10 percent levels, respectively. As the dependent variable we use the ratio of actual-to-optimal labor minus one.

Table C.3. Robustness tests OLS equity utilization depending on labor input

<i>Variable</i>	<i>Original: Labor book values + comparison with estimated values</i>	<i>RT 4: Estimated labor values (ratio of operating and labor expenses), same sample</i>	<i>RT 5: Estimated labor values, sample adapted because the estimated number exists for more insurers</i>
Intercept	0.352** (0.146)	0.356*** (0.134)	0.400*** (0.121)
SIZ	-0.016*** (0.006)	-0.004 (0.006)	-0.004 (0.005)
DIV	0.279*** (0.031)	0.278*** (0.029)	0.233*** (0.026)
GRO	0.259*** (0.046)	0.168*** (0.042)	0.175*** (0.033)
REI	0.951*** (0.047)	0.982*** (0.043)	0.915*** (0.038)
AR	0.165*** (0.049)	0.148*** (0.045)	0.196*** (0.041)
IR	-0.989*** (0.133)	-1.060*** (0.122)	-0.910*** (0.106)
OWN	0.017 (0.019)	-0.050*** (0.018)	-0.024 (0.016)
LTB	-0.092*** (0.013)	-0.136*** (0.012)	-0.122*** (0.011)
Year FE	YES	YES	YES
Sample size	8,257	8,257	9,300
Adj. R ²	0.116	0.181	0.182

Note: ***, **, and * represent significance at the 1 percent, 5 percent and 10 percent levels, respectively. As the dependent variable we use the ratio of actual-to-optimal equity minus one.

Table C.4. Robustness tests OLS labor utilization depending on labor input

<i>Variable</i>	<i>Original</i>	<i>RT 4</i>	<i>RT 5</i>
Intercept	20.917*** (1.784)	40.748*** (2.983)	44.035*** (2.853)
SIZ	-1.108*** (0.074)	-1.731*** (0.125)	-1.947*** (0.119)
DIV	-1.821*** (0.385)	-2.689*** (0.643)	-2.388*** (0.620)
GRO	1.959*** (0.558)	3.012*** (0.934)	3.719*** (0.790)
DIS	2.239*** (0.863)	2.075 (1.444)	1.040 (1.150)
HDI	-0.646*** (0.222)	-0.110 (0.371)	-0.240 (0.360)
REI	6.767*** (0.571)	-6.602*** (0.954)	-5.782*** (0.887)
AR	-0.656 (0.605)	-2.672*** (1.011)	-1.639* (0.972)
IR	3.706** (1.629)	8.256*** (2.724)	9.524*** (2.519)
OWN	1.082*** (0.240)	-4.379*** (0.402)	-4.518*** (0.396)
LTB	-1.125*** (0.162)	0.606** (0.271)	0.354 (0.257)
Year FE	YES	YES	YES
Sample size	8,257	8,257	8,257
Adj. R ²	0.145	0.298	0.297

Note: ***, **, and * represent significance at the 1 percent, 5 percent and 10 percent levels, respectively. As the dependent variable we use the ratio of actual-to-optimal equity minus one.

Table C.5. Robustness tests OLS equity utilization depending on winsorizing of regression variables

<i>Variable</i>	<i>Original: Winsorize the premium growth (GRO), the reinsurance use (REI), the ROE before the calculation of the standard deviation and the longer tailed business (LTB) to the 1% and 99% percentile.</i>	<i>RT 6: Winsorize the premium growth (GRO), the reinsurance use (REI), the ROE before the calculation of the standard deviation and the longer tailed business (LTB) to the 5% and 95% percentile.</i>
Intercept	0.352** (0.146)	0.386*** (0.148)
SIZ	-0.016*** (0.006)	-0.015** (0.006)
DIV	0.279*** (0.031)	0.283*** (0.032)
GRO	0.259*** (0.046)	0.224*** (0.081)
REI	0.951*** (0.047)	0.947*** (0.048)
AR	0.165*** (0.049)	0.173*** (0.049)
IR	-0.989*** (0.133)	-1.702*** (0.225)
OWN	0.017 (0.019)	0.012 (0.019)
LTB	-0.092*** (0.013)	-0.110*** (0.016)
Year FE	YES	YES
Sample size	8,257	8,257
Adj. R ²	0.116	0.111

Note: ***, **, and * represent significance at the 1 percent, 5 percent and 10 percent levels, respectively. As the dependent variable we use the ratio of actual-to-optimal equity minus one.

Table C.6. Robustness tests OLS labor utilization depending on winsorizing of regression variables

<i>Variable</i>	<i>Original</i>	<i>RT 6</i>
Intercept	20.917*** (1.784)	20.581*** (1.802)
SIZ	-1.108*** (0.074)	-1.117*** (0.076)
DIV	-1.821*** (0.385)	-1.797*** (0.386)
GRO	1.959*** (0.558)	4.077*** (0.989)
DIS	2.239*** (0.863)	2.376*** (0.863)
HDI	-0.646*** (0.222)	-0.569** (0.222)
REI	6.767*** (0.571)	7.178*** (0.590)
AR	-0.656 (0.605)	-0.614 (0.605)
IR	3.706** (1.629)	2.249 (2.751)
OWN	1.082*** (0.240)	1.107*** (0.241)
LTB	-1.125*** (0.162)	-1.044*** (0.191)
Year FE	YES	YES
Sample size	8,257	8,257
Adj. R ²	0.145	0.145

Note: ***, **, and * represent significance at the 1 percent, 5 percent and 10 percent levels, respectively. As the dependent variable we use the ratio of actual-to-optimal labor minus one.

Appendix D: Efficiency comparison direct vs. non-direct insurers

Table D.1. Efficiency comparison between direct and non-direct insurers

<i>Year</i>	<i>No. direct insurer</i>	<i>No. non-direct insurer</i>	<i>CE direct insurer</i>	<i>CE non-direct insurer</i>	<i>p-value Wilcoxon test</i>
1989	1	174	0.35	0.56	0.40
1990	1	179	0.25	0.54	0.21
1991	1	183	0.23	0.53	0.17
1992	1	188	0.15	0.54	0.03***
1993	5	180	0.21	0.56	0.00***
1994	4	181	0.14	0.57	0.00***
1995	5	178	0.25	0.58	0.01***
1996	6	180	0.20	0.57	0.00***
1997	8	171	0.37	0.56	0.05**
1998	7	171	0.39	0.57	0.08*
1999	6	165	0.40	0.55	0.16
2000	6	165	0.47	0.58	0.39
2001	6	159	0.52	0.57	0.68
2002	6	158	0.52	0.57	0.74
2003	6	153	0.54	0.59	0.63
2004	6	153	0.49	0.56	0.44
2005	7	141	0.58	0.60	0.90
2006	7	139	0.60	0.64	0.60
2007	7	133	0.49	0.58	0.33
2008	7	142	0.56	0.62	0.49
2009	8	141	0.48	0.59	0.27
2010	8	139	0.49	0.58	0.33
2011	8	135	0.49	0.58	0.36
2012	7	133	0.47	0.57	0.30
2013	7	133	0.46	0.57	0.28
2014	6	131	0.49	0.57	0.45
2015	5	128	0.50	0.58	0.49
All	153	4,233	0.44	0.57	0.00***

Note: ***, **, and * represent significance at the 1 percent, 5 percent and 10 percent levels, respectively. For this analysis we used the estimated equity and debt prices as well as the labor book values.

Table D.2. Efficiency comparison between direct and non-direct insurers

<i>Year</i>	<i>No. direct insurer</i>	<i>No. non-direct insurer</i>	<i>CE direct insurer</i>	<i>CE non-direct insurer</i>	<i>p-value Wilcoxon test</i>
1983	1	189	0.11	0.46	0.09*
1984	1	190	0.13	0.44	0.09*
1985	2	196	0.56	0.45	0.96
1986	2	198	0.29	0.44	0.46
1987	2	202	0.45	0.46	0.81
1988	1	204	0.24	0.47	0.17
1989	3	199	0.31	0.47	0.30
1990	3	205	0.15	0.44	0.01**
1991	3	212	0.29	0.51	0.13
1992	4	218	0.19	0.44	0.01***
1993	7	212	0.39	0.42	0.81
1994	6	214	0.39	0.44	0.26
1995	8	208	0.30	0.48	0.03**
1996	9	210	0.24	0.47	0.00***
1997	11	202	0.44	0.57	0.04**
1998	11	200	0.51	0.56	0.33
1999	10	193	0.34	0.50	0.02**
2000	10	196	0.41	0.53	0.12
2001	11	189	0.46	0.57	0.12
2002	11	188	0.50	0.48	0.60
2003	11	181	0.61	0.55	0.48
2004	10	181	0.64	0.57	0.47
2005	11	169	0.61	0.54	0.46
2006	11	167	0.59	0.57	0.74
2007	10	160	0.55	0.55	0.89
2008	11	170	0.53	0.55	0.98
2009	14	169	0.51	0.54	0.84
2010	14	168	0.47	0.50	0.81
2011	13	163	0.46	0.50	0.54
2012	13	159	0.53	0.54	0.92
2013	13	158	0.59	0.55	0.41
2014	11	157	0.58	0.54	0.48
2015	10	153	0.55	0.55	0.83
All	268	6,180	0.48	0.50	0.13

Note: ***, **, and * represent significance at the 1 percent, 5 percent and 10 percent levels, respectively. For this analysis we used the estimated equity and debt prices as well as the estimated labor number (ratio of operating and labor expenses). Therefore, more direct insurers exist.

Essay IV: The relationship between management change and firm performance: evidence from the German property and casualty insurance industry

Abstract

The paper investigates the relationship between firm performance and changes in the management board. So far, the literature has focused mainly on CEO change. We extend the scope of the literature by examining the whole management team because they also should have a significant impact on corporate value and their change may impact firm performance (Fee & Hadlock, 2004). We use a unique data set from the German property and casualty insurance industry and use efficiency scores as a firm performance measure. Our results show that firm performance is inversely related to CEO turnover but does not have affect a non-CEO change. We do not find significant evidence that firm performance improves after the CEO has been replaced. However, after there has been a change in non-CEO managers, firm performance decreases. It seems their loss seems to lessen the experience and knowledge in the management team, which has an adverse impact on firm value.

Keywords

Property and casualty insurance, data envelopment analysis, efficiency change, performance, management change

1 Introduction

As the executive board and especially the chief executive officer (CEO) define the strategy of the firm—and are therefore responsible for its future profits—the composition and changes in the executive board have long been studied in the academic literature. A large body of literature focuses on the relationship between measures of firm performance and CEO turnover. It has been found—in line with agency theory—that underperforming firms are more likely to change their CEO (e.g., Coughlan & Schmidt, 1985; Warner, Watts, & Wruck, 1988; Puffer & Weintrop, 1991; Murphy & Zimmermann, 1993; Huson, Parrino, & Starks, 2001; Farrell & Whidbee, 2003). In addition, scholars investigate the impact of outside directors (e.g., Weisbach, 1988) and differences among industries (e.g., Parrino, 1997) on the dismissal of the CEO. Furthermore, researchers analyze whether or not CEO turnover significantly improves firm performance in the next periods (e.g., Denis & Denis, 1995; Huson, Malatesta, & Parrino, 2004; He, Sommer, & Xie, 2011). In contrast to the large number of studies on CEO turnover, evidence for the executive team is quite sparse. Some scholars study changes in the executive board after weak performance (e.g., Blackwell, Brickley, & Weisbach, 1994; Fee & Hadlock, 2004), and only Furtado and Rozeff (1987) and Mian (2001) investigate firm performance in the aftermath. As non-CEOs should also have a significant influence on the corporate value, understanding this change and its impact is also an important topic to investigate (Fee & Hadlock, 2004).

This paper extends and contributes to the limited literature on the effect of firm performance on changes in the management board and on the influence of changes in the management board on firm performance. We first investigate if poor firm performance triggers CEO and non-CEO changes. We then analyze if a new CEO and new non-CEO board members improve future firm performance. With our paper, we shed light on the discussion of how CEOs and non-CEOs are evaluated—if CEOs, the entire management team, or only non-CEOs are held responsible for bad firm performance. In a classical principal-agent setup (Holmström, 1979), firm performance serves as an indicator of managers' actions, abilities, and invested effort (Fee & Hadlock, 2004). However, it is hard to say if the management board works as a team or if the CEO alone makes most decisions. If it is evaluated as a team effort, bad firm performance should correlate with CEO and non-CEO dismissal. If not, firm performance may not be suitable for measuring the ability and effort of non-CEOs and we should not expect to find a direct relation (Fee & Hadlock, 2004). Moreover, when the CEO is quite powerful, it is also possible that only non-CEOs have to face the consequences and are dismissed (Fee & Hadlock, 2004). If poor firm performance is the fault of the management team and if control mechanisms are effective, corporate value should improve after the management team has been replaced (e.g., Denis & Denis, 1995).

Therefore, we analyze if replacing managers proves a good decision in terms of leading to better firm performance after their dismissal.

We consider the management board composition for German property and casualty (p/c) insurance companies from 1979 to 2015. According to He et al. (2011), focusing only on a single industry allows a clear identification and a lower risk of omitting variables. Moreover, Leverty and Grace (2012) argue that p/c insurers often experience financial distress, thus, offering good data to study the impact of management changes on firm performance and vice versa. Furthermore, the insurance industry is characterized by the coexistence of stock and mutual companies, allowing us to analyze corporate governance differences between these two distinct legal forms. The focus on Germany makes our study one of the few outside of the U.S. context and has the advantage to offer clear distinction between the management (*Vorstand*) and the supervisory (*Aufsichtsrat*) board with its two-tier board system. The supervisory board monitors the activities of the management board and appoints its members. Therefore, monitoring can be more efficient because of independent boards or less efficient because of higher information asymmetries. Our paper is one of the few analyzing the effectiveness of internal control mechanisms in the two-tier board system.

We manually collect the data of all p/c insurers from annual reports for 1979 through 2015 as published in the *Hoppenstedt Versicherungsjahrbücher*. We use cost and revenue efficiency scores as our measures of firm performance. These are two often-used performance measures in the insurance industry (for an overview see, e.g., Cummins & Weiss, 2013). So far, to the best of our knowledge, only He et al. (2011) have used efficiency scores in the context of firm performance and management change. Relying on efficiency scores instead of classical performance measures or stock prices offers several advantages. One is that we can include all insurers and are not restricted to publicly traded companies. Compared to classical accounting performance measures, efficiency scores more accurately reflect the production process (He et al., 2011) and are harder for management to manipulate. To calculate the efficiency scores, we use data envelopment analysis (DEA), which—based on a benchmark mechanism—compares firms against the best-in-class firm(s). Because of this benchmarking mechanism, efficiency scores are comparable to relative performance measures as they consider the output of other insurers. As a robustness test, we also include the relative return on equity (ROE), which is the insurer-specific ROE divided by the best overall ROE in a given year.

We employ probit regression to measure the effect of firm performance on the probability of CEO or non-CEOs change and use multivariate regression to measure the effects on firm performance after change(s) in the CEO or management board. We find that the probability of the CEO leaving increases after an insurer has performed poorly.

However, we do not find this inverse relationship between firm performance and non-CEOs change. This finding suggests that non-CEOs dismissals are typically not a consequence of poor efficiency changes. One reason for our finding could be that efficiency changes are a noisier signal for the efforts and abilities of non-CEOs (Fee & Hadlock, 2004). After the change in CEO, we do not find significant evidence that efficiency increases. This may be caused by the limited influence of the new CEO. However, we find that efficiency decreases after non-CEOs change. A reason could be that their replacement lessens the know how in the management.

The remainder of this paper is organized as follows. In Section 2, we discuss the relevant literature and theoretical background. In Section 3 we present our hypotheses. Section 4 outlines the methodology and data. In Section 5 we discuss the empirical results and Section 6 concludes.

2 Literature review

In this section, we begin by presenting the literature on the relationship between firm performance and management changes from cross-industry studies. In Section 2.3, we discuss three studies that investigate management change in the insurance industry.

2.1 The impact of firm performance on management turnover

To resolve the classical principal-agent conflict (Holmström, 1979), the principal has to monitor the agent, which is costly. To decrease those costs, the principal relies on monitoring by the board of directors or the supervisory board (in Germany). With intact corporate governance and efficient monitoring of executives' work, firm performance is an indicator of a manager's ability and effort. Thus, unsatisfactory firm performance suggests that the CEO lacks ability and competence, which may harm shareholder's (i.e., the principal's) value. Indeed, a large stream of literature has shown that after a firm has performed poorly, the probability of a CEO change is significantly higher. Furthermore, scholars have investigated which corporate governance structures would increase the board's ability to monitor the management (Huson et al., 2001). Because of high-quality and comprehensive data sources, most papers analyze the relation between stock price performance and CEO turnover for U.S. publicly traded companies.

Coughlan and Schmidt (1985) argue that incentives for managers should be constructed in a way that gives managers an incentive to increase shareholder value. Otherwise firms would face higher costs in raising capital as capital markets are quite competitive. This could, for example, be achieved by linking CEO compensation to stock price performance. In consequence, the (supervisory) board should discipline the CEO for actions that harm shareholder value, thereby making bad firm performance a predictor for CEO change. Coughlan and Schmidt (1985) find a substantial inverse relationship between stock price performance and CEO turnover. Warner et al. (1988) present further

support for this relationship by extending their sample to the chairman and president of the board. However, unless stock price performance is extremely poor, they argue that management turnover is difficult to predict. Recent studies have extended the focus on performance; for example, Leone and Liu (2010) and Hazarika, Karpoff, and Nahata (2012) analyze the impact of earnings management on CEO turnover. Using firm performance as a control variable, both studies support the significant negative relationship between performance and CEO turnover.

Analyzing the effectiveness of boards, Weisbach (1988) tests the role of inside and outside members of the board of directors. His results support the hypothesis that outside members have an incentive to develop reputation as good controllers and therefore, are more sensitive to firm performance. Furthermore, Weisbach (1988) investigates if stock prices are a good measure of firm performance in relation to CEO performance. He argues that if investors already expect an unsatisfactory CEO to resign, they may also expect the resignation to be followed by higher firm value. Thus, the stock price might not fully reflect the CEO's ability. Indeed, Weisbach (1988) finds evidence that the boards of directors look at unbiased accounting measures when evaluating firm performance. However, if outside directors are too busy, for instance, because they are controlling too many corporations, the sensitivity decreases (Fich & Shivadasani, 2006).

In another sensitivity analysis, Li and Srinivasan (2011) compare boards with founders and without; they find that controlling mechanisms with founder board members are even more effective. However, founder CEOs are less likely to be fired (Leone & Liu, 2010). Adding to the sensitivity analyses, Parrino (1997) reports that the likelihood of a forced turnover is higher in more homogenous industries (e.g., metal mining, oil and gas extraction, and air transportation) as replacement costs are lower.

Using data from private equity-backed firms in Central and Eastern Europe and Central Asia, Cornelli, Kominek, and Ljungqvist (2013) show that soft information (i.e., the feeling of incompetence) play a larger role than hard performance measures when learning about a CEO's abilities and efforts. Therefore, the decision to dismiss a CEO may not always be based on bad firm performance.

Scholars have also examined the relationship between industry performance and CEO turnover. So far, the empirical evidence is mixed. Morck, Shleifer, and Vishny (1989) and Barro and Barro (1990) find that the board considers only firm performance; in contrast, Warner et al. (1988) and Jenter and Kanaan (2015) argue that industry performance should also be evaluated. According to Jenter and Kanaan (2015) there could be many reasons, for example, shareholders pressure the board of directors to replace the CEO when the stock price is down, even though the firm's underperformance is not necessarily the CEO's fault. Moreover, it could be a rational response to changing

market conditions, such as an economic downturn, which requires a CEO to possess a different set of skills (see also Eisfeldt & Kuhnen, 2013).

Research on the impact of firm performance on executive turnover below the CEO does not seem to have been exhausted. This seems quite surprising, since the whole executive team should have a significant influence on firm value; it seems worth investigating whether or not non-CEOs are also held accountable. In a study of larger corporations in the U.S., Fee and Hadlock (2004) find that the change in non-CEOs is less sensitive to firm performance than the change in CEOs. But their research suggests that the change is triggered by the departure of the CEO, especially if the new CEO comes from outside the firm. Although they conclude that firm performance may be a noisier signal for non-CEOs and that they are evaluated differently, they leave the evaluation factors as an open research question.

In contrast, more industry- and function-specific studies find that the management board is evaluated as a team and that firm performance is negatively related to non-CEO change. For example, Blackwell et al. (1994) study subsidiary bank managers and find an inverse relation between subsidiary performance and manager change. Fee and Hadlock's (2000) investigation of the U.S. newspaper industry has found a significant negative relationship between performance and turnover probability for some management positions. In a more function-specific study, Mian (2001) shows that CFO turnovers can also be triggered by negative firm performance. Leone and Liu (2010) and Hazarika et al. (2012) explore the CFO change in their studies of earnings management. Their regression results suggest that poor firm performance leads to CFO changes.

In summary, many studies find that negative firm performance leads to the change of the CEO, thus the internal monitoring seems to be efficient and can be improved by structural changes. However, the evidence in a non-U.S. setting and on non-publicly traded firms is to the best of our knowledge quite sparse. Furthermore, we extend the analysis to the entire management board, something that only a few studies have done.

2.2 Firm performance after management turnover

If internal control mechanisms are effective and if underperforming managers leave the firm, firm performance should improve (Denis & Denis, 1995; He et al., 2011). In contrast, it could be argued that the CEO's influence is too limited, especially in larger and more complex firms, to have a significant effect on firm performance, at least in the short term. And indeed, whereas the empirical literature is quite clear on the inverse relationship between prior firm performance and CEO turnover, the empirical evidence regarding firm performance after leadership changes is quite mixed.

For example, Lieberman and O'Connor (1972) show that environmental or organizational factors influence firm performance more than management change.

Using a different methodology and measures of environmental and organizational factors, Weiner and Mahoney (1981) find that leadership change does indeed influence performance.

However, according to Beatty and Zajac (1987) the results from Weiner and Mahoney (1981) should be interpreted with caution, because their sample consists of firms with different fiscal years and because they combine accounting data with stock market information. For this reason, Beatty and Zajac (1987) examine stock price reaction after the announcement of the CEO change. They find that CEO turnover announcements have a negative influence on firms' stock prices. Khanna and Poulson (1995) support the results of Beatty and Zajac (1987). They compare financially distressed firms with a control group and find a significant negative stock market reaction after CEO turnover for both groups. Their evidence suggests that CEOs who have been dismissed are blamed for a firm's prior underperformance.

In contrast, focusing on such firms, Bonnier and Bruner (1989) find a significant positive abnormal stock return after the CEO turnover. Bonnier and Bruner (1989) argue that the sample of financial distressed firms reduces the information effect (i.e., the announcement indicates to shareholders that a firm's performance is weak). Weisbach (1988) also finds a positive stock market reaction when the board is dominated by outsiders, consistent with his hypothesis that outsider-dominated boards are better at firing underperforming CEOs. However, Khanna and Poulson (1995) find no differences between outsider- and insider-dominated boards.

Reinganum (1985) and Warner et al. (1988) find no significant stock price reaction to the announcement of CEO change. Reinganum (1985) reports only a significant positive impact for small firms, when the announcements of a CEO's departure are accompanied by information on an external successor.

Bonnier and Bruner (1989) and Huson et al. (2004) are not surprised by the mixed empirical evidence on the impact of CEO change and resulting stock market performance. They argue that negative performance could be driven by investors who attribute poor performance to the change in management. In contrast, good performance may be driven by the expectation of better management, which increases firm value.

Hotchkiss (1995), Denis and Denis (1995), Huson et al. (2004) and Cornelli et al. (2013) use accounting measures to overcome the issues of stock market information. They all show that firm performance improves after CEO turnover.

Hotchkiss (1995) considers only financially distressed firms, so the results probably cannot be generalized. Dennis and Dennis (1995) find that performance improvement—measured as unadjusted and industry-adjusted operating return on assets (ROA)—is even stronger when CEOs are forced to leave the firm. However, they consider only the

years from 1985 through 1988. To expand Denis and Denis' (1995) findings to a longer sample period, Huson et al. (2004) investigate the years 1971–1994. They find that the ROA increases significantly only when they adjust for similar control firms.⁸⁵ Moreover, Huson et al. (2004) show that abnormal positive stock returns are significantly positive in relation to subsequent operating performance. Cornelli et al. (2013) find that intervening boards make a profitable private equity investment more likely.

Most empirical analyses of firm performance after management turnover are—to the best of our knowledge—limited to CEO turnover. Exceptions are Furtado and Rozeff's (1987) examination of the four top executives in the board of directors (chairman, vice-chairman, president, and CEO) and Mian's (2001) analysis of CFO turnover. Furtado and Rozeff (1987) find a small positive reaction; Mian (2001) finds an insignificant stock price reaction.

To summarize, the empirical evidence on stock price reaction after management is mixed. However, recent studies using accounting performance measures (i.e., operating income) find a significant positive relation. We extend the literature by analyzing the impact changes in the management board on efficiency changes, which, to the best of our knowledge, only He et al. (2011) have analyzed so far.

2.3 Evidence from the insurance industry

Evidence from the insurance industry is quite sparse. The main body of literature focuses on different corporate governance indicators (e.g., organizational structure, board compensation, outside vs. insider directors, ownership structure) and their impact on the risk-taking behavior of the insurers (e.g., Cheng, Elyasiani, & Jia, 2011; Ho, Lai, & Lee, 2013; Eling & Marek, 2014).

With respect to CEO turnover and firm performance in the insurance industry, there are, as far as we know, only three studies. Two of the studies use the U.S. p/c insurance industry to compare and contrast organizational structures. The different organizational forms of insurance companies make it possible to assess the control mechanisms not only for stock but also for mutual insurers. Cheng, Cummins, and Lin (2017) argue that mutuals have fewer corporate governance mechanisms⁸⁶ and thus weaker possibilities to discipline the management. They expect that boards of mutual insurers to be less sensitive to a firm's poor performance.

⁸⁵ In contrast to Denis and Denis (1995), Huson et al. (2004) find, that the industry-adjusted ROA increases only weakly and that the unadjusted ROA is negative after the CEO change.

⁸⁶ Whereas stock insurers are controlled internally by the supervisory board, externally by the capital market and are threatened by takeover in case of weaker performance, mutual insurers are only controlled internally (He & Sommer, 2011; Cheng et al, 2017).

In their analysis of the impact of insurers' performance on CEO turnover, He and Sommer (2011) find that the impact of poor performance and subsequent nonroutine (i.e., the CEO does not remain in the board of directors) CEO turnover is stronger for stock than mutual insurers. However, using data from 1996 to 2004, they do not find any evidence that an outsider-dominated board or a dual CEO (meaning a CEO and chairman of the board) increases the impact of performance on CEO turnover, concluding that ownership structure plays a more important role. He and Sommer (2011) use operating (=income before taxes plus dividends to policyholders) and underwriting (=operating income minus investment income) ROA as their performance measure.

By extending He and Sommer (2011), Cheng et al. (2017) decompose stock insurers into publicly and non-publicly traded stock insurers. Because they think that there are different control mechanisms in stock insurers, they subdivide non-publicly traded insurers even further into family-owned (with and without family CEO) and non-family-owned. They show that family-owned stock insurers with family CEOs have the lowest turnover rate, even lower than that of mutual insurers. Cheng et al. (2017) also show for the period 1993–2006 that the insurers' board of directors filters out the industry performance, thus, supporting Morck et al. (1989) and Barro and Barro (1990) and contrasting the recent study from the work of Jenter and Kanaan (2015). In line with He and Sommer (2011), they use ROA as performance measure.

He et al. (2011) focus on post-performance after CEO turnover. Using efficiency scores as performance measure, they find that between 1996 and 2004 the performance of insurance firms improved after the CEO was replaced. Their results are stronger for nonroutine changes. Even though it is not the focus of their study, they find evidence that revenue efficiency scores have some power to predict change in CEO.

Our study contributes to the literature on the relationship of pre-performance and CEO turnover. We also extend the small body of literature on firm performance after the CEO has been changed. Furthermore, we investigate these relationships with respect to other members of the management board, thus adding to this body of literature, too. As discussed before, this is one of the few studies in a non-U.S. setting and, as far as we know, the first to analyze the German p/c insurance market in relation to CEO turnover. Thus, we explore the effectiveness of other corporate governance systems and regulatory regimes. We also contribute to the discussion of effective corporate governance in different organizational forms. As we have limited our scope to the insurance industry, we have a more homogeneous sample than previous studies and the risk of omitted variables is reduced (He et al., 2011; He & Sommer, 2011). Table 15 summarizes the relevant empirical literature.

Table 15. Summary of existing literature

	<i>Non-insurance</i>	<i>Insurance</i>
<i>CEO change</i>	Performance → Turnover: • Coughlan and Schmidt (1985) • Warner et al. (1988) • Weisbach (1988) • Morck et al. (1989) • Barro and Barro (1990) • Parrino (1997) • Huson et al. (2001) • Leone and Liu (2010) • Hazarika et al. (2012) • Cornelli et al. (2013) • Jenter and Kanaan (2015) Turnover → Performance: • Lieberman and O'Connor (1972) • Weiner and Mahoney (1981) • Reinganum (1985) • Beatty and Zajac (1987) • Warner et al. (1988) • Weisbach (1988) • Bonnier and Bruner (1989) • Denis and Denis (1995) • Hotchkiss (1995) • Khanna and Poulson (1995) • Huson et al. (2004) • Cornelli et al. (2013)	Performance → Turnover: • He and Sommer (2011). • Cheng et al. (2017). Turnover → Performance: • He et al. (2011).
<i>Management change</i>	Performance → Turnover: • Blackwell et al. (1994) • Fee and Hadlock (2000) • Mian (2001) • Fee and Hadlock (2004) • Leone and Liu (2010) • Hazarika et al. (2012) Turnover → Performance: • Furtado and Rozeff (1987) • Mian (2001)	<i>none</i>

3 Hypotheses

In Germany, the supervisory board monitors the activities of the management board and appoints its members. Empirical studies, mainly concerned with U.S. stock firms and U.S. p/c insurers, have shown that internal control mechanisms work well to discipline managers and thus reduce the monitoring costs for principals (e.g., Coughlan & Schmidt, 1985; Warner et al., 1988; Huson et al., 2001; Huson et al., 2004). Based on their results, we state our first hypothesis for German p/c insurers:

Hypothesis 1: *The performance of German p/c insurers is inversely related to the probability of CEO turnover.*

Additionally, we analyze the impact of negative firm performance on non-CEOs turnover. In a classical principal-agent setting, internal monitoring mechanisms should control the capabilities of non-CEOs in the management board. However, it is not clear if firm performance serves as a good measure. If an insurer's performance is evaluated as a team effort, CEO and non-CEOs should be held responsible for a firm's poor performance. If this is the case, we should see a direct relation between our efficiency scores and non-CEOs dismissal. The team effort hypothesis is supported by some industry-specific studies (e.g., Blackwell et al., 1994; Fee & Hadlock, 2000). Fee and Hadlock (2004) argue that firm performance could be a noisier signal for non-CEOs ability as they find a less sensitive relationship between performance and non-CEO changes.

In our analysis, we define non-CEOs change as one-third of the members of the management board (except the CEO) leaving the firm.⁸⁷ We use this relative measure to account for different board sizes among the insurance firms. In larger board, non-CEOs leaving at the same time would be in line with the team hypothesis. Thus, we follow the more industry-specific studies and propose our second hypothesis:

Hypothesis 2: *Firm performance is inversely related to the probability of managers leaving the management board.*

In line with the presented empirical studies, internal control mechanisms seem useful and effective. In consequence, an effective control mechanism should be able to find and hire more competent successors, who then improve firm performance (Denis & Denis, 1995). In addition, He et al. (2011) argue that success could take several years. However, their results suggest that in forced turnovers, performance improves right after

⁸⁷ When at least one non-CEO is leaving the management board, we calculated the relative number of non-CEO(s) leaving by $\# \text{ non-CEO(s) leaving} / \# \text{ of non-CEOs in the board}$. We use the median of this relative number (33 percent) as our threshold because we want to make sure that the change is severe and not driven by many small changes in the board.

the CEO leaves the insurer. Therefore, we expect similar results and formulate our third and fourth hypotheses:

Hypothesis 3: *After CEO turnover, we expect firm performance to improve.*

Hypothesis 4: *After non-CEOs leaving, we expect firm performance to improve.*

Alternatively, as we measure only severe non-CEO changes, managers leaving the insurer could also have a negatively impact on firm performance, because they have amassed a great deal of knowledge about the insurer's operations.

4 Sample data and methodology

4.1 Data sources

The data used in our study are extracted from the annual reports from 1979 to 2015 published in the *Hoppenstedt Versicherungsjahrbücher* (e.g., Luhn, 2009; Mahlberg & Url, 2010; Braun, Schmeiser, & Rymaszewski, 2015). The *Hoppenstedt Versicherungsjahrbuch* includes all annual reports for almost every re-/insurance company in Germany. For our purposes, we consider only the p/c insurance industry (excluding health insurers). The annual reports include all relevant firm-level information (e.g., financial data, organizational form, names of the management and supervisory board members). As there is no digital source for the years 1979 through 2010, we manually collected the firm-level data from physical books. From the managers' names, we can determine the tenure of CEO and management board members as well as the year of changes in the CEO and management board membership.⁸⁸

The CEO turnover variable is defined as a dummy variable that equals 1 for year t if the reported name of the CEO in year t is different from in year $t - 1$, otherwise it equals 0.⁸⁹ Following Cheng et al. (2017), we set the dummy variable equal to 0 if it is a turnover of an interim CEO, i.e., the CEO is holding the position only for a year. We also distinguish routine (i.e., CEO changes to the supervisory board) from nonroutine turnover in our analysis.

The executive member turnover dummy variable is defined similarly, as equal to 1 for year t if at least one third of the members of the management board (except the CEO) leave the firm. With this definition, we make sure that the change is severe and depends on board size. Otherwise, we would have a lot of noise as managers quite often leave

⁸⁸ The *Hoppenstedt Versicherungsjahrbücher* provide information on *Vorstandsvorsitzender* and *Sprecher*, which we both define as the CEO function. However, sometimes this information is not given. In this case, we look at the function in the previous and subsequent year. If the function in both years is equal, we will assign the same function in the sample year. If we do not have any information given, we define the first person in the name list as CEO, assuming that the information are ordered by important board functions.

⁸⁹ We verified our assumption, that the turnover event happens in year t with a sample test.

the management board. Additionally, for the analysis of the impact of board changes on firm performance, the number of managers leaving the board has to be equal to the number of new managers joining the board.

For the efficiency analysis, we collect input and output price information from multiple sources. We obtain price indices information from *Deutsche Bundesbank* and the compensation data from the German national account published by the Federal Statistical Office (Destatis).⁹⁰ All monetary values are deflated to 2015 values and the values prior the year 2000 are converted into EUR values.

As the DEA demands positive inputs and outputs, we exclude all insurers whose data do not fulfill this requirement. Therefore, for the DEA analysis we have 7,174 firm years. Furthermore, we exclude firms that have no information on the executive board, which reduces the firm years by 94. The final (unbalanced) sample consists of 310 p/c insurers with data on 7,080 firm years. However, as we use lagged dependent variables in our regression analysis the number of observations is reduced. We report the sample size in each table of results.

4.2 Firm performance

Instead of stock price performance or accounting measures, we use the bias-corrected efficiency⁹¹ levels of the insurance firms as our performance measure. Efficiency levels allow us to analyze private and public traded companies, thus, we do not have to limit our analysis to stock insurers (Leverty & Grace, 2012). Furthermore, efficiency scores consider the complex production process and therefore, are more informative than simple accounting measures (He et al., 2011).

Farrell (1957) defines a fully efficient firm as the best practice or benchmark firm, meaning that no other firm uses less input to produce the same amount of output. Therefore, efficiency does not reflect a theoretically possible outcome. Instead, firms are compared to each other. All efficient firms built an efficient frontier, so every firm on that frontier has an efficiency score of 1. Every firm not operating on the efficient frontier has an efficiency score between 0 and 1. To determine the efficient frontier, we use non-parametric mathematical programming approach—data envelopment analysis (DEA)—which measures firm productivity against the productivity of best-practice

⁹⁰ For the time period 2000–2017 this data is directly available. For 1991–2000 we use the compensation growth rates from a different sector including the financial service industry per federal state and apply them to the given compensation values from the year 2000. Prior the year 1991, we do not have compensation data per federal state, thus we apply the German compensation growth rates of this sector till 1979.

⁹¹ We apply the bootstrap approach introduced by Simar and Wilson (2007) to estimate the efficient frontiers. Thus, we consider the sensitivity of efficiency measures to sampling variation.

firms (Charnes, Cooper, & Rhodes, 1978).⁹² Following the argument of He et al. (2011) that the primary objective of insurers is to maximize profits by either minimizing costs or maximizing revenue, we concentrate on cost (CE) and revenue efficiency (RE). Hence, cost minimization focuses on the right amount of inputs to produce a given output (i.e., input orientation) and revenue frontiers focus on maximizing revenues by holding inputs constant (Cummins & Weiss, 2013).

To calculate the CE of an insurer s ($s = 1, 2, \dots, S$), we first must determine its optimal input mix I^{s*} , which is given by the solution x ($M \times 1$) of the following linear problem (assuming variable return to scale):

$$(13) \min_{x, \lambda^s} (p^s)^T x, \text{ subject to } O\lambda^s \geq O^s, x \geq I\lambda^s, \lambda^s \geq 0, 1^T \lambda^s = 1,$$

where p^s is an $M \times 1$ input price vector of insurer s , I is an $M \times S$ input matrix used by all insurer in the sample, O is an $N \times S$ matrix of all outputs produced by all insurer and O^s is the $N \times 1$ output vector for insurer s . The vector λ^s is a $S \times 1$ intensity vector for insurer s used to construct the optimal insurer s^* , which uses the optimal input mix I^{s*} . Let p_i^s be the price and I_i^s is the amount of input i . Then the CE for insurer s is defined as:

$$(14) CE^s = \frac{\sum_{i=1}^M p_i^s I_i^{s*}}{\sum_{i=1}^M p_i^s I_i^s}.$$

The estimation of revenue efficiency is quite similar. But instead of comparing firms with similar output levels, we compare firms with similar inputs levels and maximize the output amount. Thus, the linear optimization program for insurer s to calculate its revenue efficiency is given by:

$$(15) \max_{y, \lambda^s} (r^s)^T y, \text{ subject to } O\lambda^s \geq y, I^s \geq I\lambda^s, \lambda^s \geq 0, 1^T \lambda^s = 1,$$

where we define r^s as an $N \times 1$ output price vector of insurer s . Analogously, revenue efficiency is defined as:

$$(16) RE^s = \frac{\sum_{i=1}^M r_i^s O_i^s}{\sum_{i=1}^M r_i^s O_i^{s*}}.$$

4.2.1 Input and input prices

We follow p/c insurance efficiency studies, where equity capital and technical reserves (i.e., debt capital) as well as labor are frequently used as input variables (e.g., Luhnén, 2009; Mahlberg & Url, 2010; Eling & Schaper, 2017). As most of the German p/c insurers are not publicly traded, the cost of equity cannot be individually estimated from market data. Instead we approximate the cost of equity capital uniformly for every

⁹² Many scholars have used DEA to measure the performance of insurers. We refer to Eling and Luhnén (2010), Cummins and Weiss (2013) and Kaffash, Azizi, Huang, and Zhu (2020) for comprehensive reviews regarding the insurance industry.

insurer by the 7-year average return of the German stock index (DAX).⁹³ Technical reserves are the largest share of debt capital and therefore, the costs of debt capital are reflected in premiums and dividend payments to policyholders (Cummins & Weiss, 2013). Following Luhnén (2009), we calculate the price of debt capital using the 7-year average return of the Deutscher Rentenindex (REX), which reflects the interests of German government bonds. As we do not want to exclude any insurer because of missing labor numbers, we estimate the numbers of employees by dividing the total operating expenses by the price of labor.⁹⁴ For the price of labor, we use the yearly compensation per employee for the financial service industry, which includes the gross wage and social security contributions paid by the employer. We use the compensation data of the federal state, where the headquarters are located.

4.2.2 Output and output prices

We follow the value-added approach, which is the standard method for measuring intangible insurance outputs (see e.g., Cummins & Weiss, 2013). Insurance companies provide three services to the insured: 1) risk-pooling and -bearing; 2) financial services; and 3) financial intermediation. We use net losses (i.e., paid losses plus additions to reserves) as our proxy for the risk pooling and financial service functions. We determine the price of the net losses as the difference of net premiums and net losses divided by net losses (see e.g., Mahlberg & Url, 2010; Cummins & Weiss, 2013). Additionally, we apply the smoothing procedure from Cummins and Xie (2008) to correct for the “errors in variables” problem in losses and loss prices. Total investments serve as our proxy for the intermediation function. For the price of total investments, we also use the 7-year average return of the REX.⁹⁵ Table 16 presents the summary statistics of our input (output) and input (output) prices.

⁹³ Similar approaches have been used by Luhnén (2009), Mahlberg and Url (2010), Biener, Eling, and Wirfs (2016) and Eling and Schaper (2017). Cummins and Xi (2008) compare efficiency scores when using size and risk adjusted capital costs with efficiency scores when using, for example, uniformly an index. The authors obtain for both approaches similar results.

⁹⁴ This approach has also been adopted by, among others, Cummins, Rubio-Misas, and Zi (2004), Luhnén (2009), Biener and Eling (2011) and Eling and Schaper (2017).

⁹⁵ Mahlberg and Url (2010) present evidence from the German supervisory authority that only 3 percent of the insurer’s portfolio is held in stocks. The rest is held in debt instruments. As we do not have a corporate bonds index over the whole sample period, we use the REX. However, as insurers mainly invest in secure assets, we argue that return on German government bonds is a good measure.

Table 16. Summary statistics for inputs, input prices, outputs, and output prices
(1979–2015, 7,174 firm years, 2015 real values)

<i>Variable</i>	<i>Unit</i>	<i>Mean</i>	<i>St. Dev.</i>	<i>Min</i>	<i>Max</i>
Input					
Equity capital	TEUR	103,701	249,339	71	3,162,651
Debt capital	TEUR	362,520	1,145,680	1	19,638,136
Labor	Quantity	841	2107	0.01	34,145
Input prices					
Equity capital costs	%	11.0	6.1	0.1	25.5
Debt capital costs	%	6.9	1.6	4.1	9.7
Labor wages	EUR	66,259	6,104	44,439	91,257
Output					
Losses incurred	TEUR	147,716	361,675	3	5,418,844
Invested assets	TEUR	494,627	1,489,854	324	29,486,423
Output prices					
Losses incurred	%	47.8	0.5	46.9	48.6
Invested assets	%	6.9	1.6	4.1	9.7

4.3 Regression analysis

4.3.1 Impact of firm performance on management board changes

We investigate the effect of efficiency change on CEO or executive turnover by looking at the 1-year lagged change of *CE* and *RE* values as empirical evidence suggests that boards react quite quickly to poor firm performance.⁹⁶ The *CE* (*RE*) change is defined as the ratio of the *CE* (*RE*) score at $t - 1$ and the *CE* (*RE*) score at $t - 2$.⁹⁷ To analyze the effect, we use a probit regression model (e.g., as used in Cheng et al., 2017) and include several control variables, which the previous literature has found to have an impact on CEO turnover:

$$(17) TO_t^s = \beta CE_{t-2,t-1}^s + \gamma X_{t-1}^s + \varepsilon_t^s,$$

$$(18) TO_t^s = \beta RE_{t-2,t-1}^s + \gamma X_{t-1}^s + \varepsilon_t^s$$

where TO_t^s represents the dummy variable of the CEO or management board member turnover of insurer s in year t . $CE_{t-2,t-1}^s$ ($RE_{t-2,t-1}^s$) represent the change in cost (revenue) efficiency from $t - 2$ to $t - 1$ and X_{t-1}^s is the vector of firm-specific (lagged) control variables. β and γ are the parameters to be estimated. This regression analysis allows us to test the impact (significant or insignificant) and direction (positive or negative) of the change in efficiency and other firm specific factors. For robustness, we include the 1-year lagged relative ROE (i.e., insurer-specific ROE divided by the best overall ROE in a given year).

⁹⁶ In line with the internal control mechanism, CEO dismissals should happen immediately after poor performance (Weisbach, 1988). Thus, it seems compelling to only include a 1-year lag. This is supported by Murphy and Zimmerman (1993) and He and Sommer (2011), who find no significance between the 2-year lagged performance variable and CEO turnover.

⁹⁷ This approach is inspired by He et al. (2011), who use efficiency change as a dependent variable in their post-turnover regression.

Following the U.S. studies by He and Sommer (2011) and Cheng et al. (2017), we include as lagged control variables the line-of-business Herfindahl index (DIV), leverage (LEV), the natural logarithm of total assets (SIZE), the reinsurance use (REI), and a mutual indicator (OWN).⁹⁸ Additionally, we control for the average tenure of non-CEO members (BOARD EXP) and CEO experience (CEO EXP) (i.e., the number of years the managers is appointed as CEO). We describe the previous findings on the impact of these control variables on the CEO turnover. We assume that their impact on management turnover is the same.

By including the line-of-business Herfindahl index (H-index), we control for the insurer's diversification: the lower the H-index the higher the diversification. The H-index has been used as a measure of business complexity (He & Sommer, 2011; Cheng et al., 2017). Parrino (1997) argues that more complex business is related to a lower probability of CEO turnover; however, empirical evidence by He and Sommer (2011) and Cheng et al. (2017) support this idea for turnovers only where the CEO leaves the firm.

We include leverage as a measure of firm risk and the natural logarithm of total assets as a measure of firm size. Both variables could be related to the complexity of business, thus a negative relationship is expected. Indeed, Blackwell et al. (1994) document this relationship in the banking industry. However, for the insurance industry, this relationship has not been confirmed. For example, He and Sommer (2011) find a significant positive and Cheng et al. (2017) document an insignificant relationship.

He and Sommer (2011) find that reinsurance usage is positively related to CEO turnover because it offers protection against an income shock and severe negative firm performance. However, these results are not confirmed by Cheng et al. (2017), because they do not find a significant relationship.

As stock companies are more closely monitored, for example, by stock market investors, the likelihood of a CEO turnover should be higher for stocks. This argument is supported by He and Sommer (2011). Cheng et al. (2017) are concerned with the analysis of different ownership forms on CEO turnover. They break down different forms of stock ownership and find that family firms with family board members have the lowest turnover. Therefore, their results are consistent with the argument that more lax monitoring leads to lower turnover. To examine the sensitivity of performance and organizational form, we include the interaction term of both variables.

⁹⁸ The ratio of outside directors to inside directors is often used as another control variable (see e.g., Weisbach, 1988; He & Sommer, 2011), but as we do not have any additional information on the non-executive members, we cannot make the distinction.

To control for board characteristics, we add the average tenure of the executive board and the CEO tenure in our turnover analysis. The CEO tenure variables should be positively correlated with CEO change as it is also an indication of the CEO's age. The board tenure variable in CEO turnover regression could indicate how easily the CEO can be replaced by board members, because the board is experienced enough to compensate for the loss of knowledge. Thus, we would also expect a positive relationship.

4.3.2 Influence of changes in the management board on firm performance

To analyze the effect of CEO or non-CEO turnover on firm performance, we follow the approach from He et al. (2011) and use the CE and RE changes in the three windows $(t - 1, t + 1)$, $(t - 1, t + 2)$ and $(t - 1, t + 3)$ as our dependent variable. We use the following multivariate regression model – for simplicity only displayed for the $(t - 1, t + 1)$ window):

$$(19) \quad CE_{t-1,t+1}^s = \beta TO_t^s + \gamma X_{t-1}^s + \delta T_{t-1} + \varepsilon_t^s,$$

$$(20) \quad RE_{t-1,t+1}^s = \beta TO_t^s + \gamma X_{t-1}^s + \delta T_{t-1} + \varepsilon_t^s$$

where $CE_{t-1,t+1}^s$ ($RE_{t-1,t+1}^s$) is the efficiency change between $t - 1$ and $t + 1$ and TO_t^s is the dummy variable indicating a management turnover in year t . As lagged control variables we use the diversification of business line (DIV), leverage (LEV), total assets (SIZE), a mutual dummy (OWN), board tenure (BOARD EXP) and CEO tenure (CEO EXP). However, as we regress on efficiency changes and not efficiency values, their impact cannot clearly be derived from empirical efficiency studies (e.g., Luhnén, 2009, Biener et al., 2016). The results from He et al. (2011) suggest that SIZE, LEV and OWN have a negative and DIV has a positive impact on efficiency changes.⁹⁹ The argument for the inclusion of CEO EXP is that an experienced CEO could be hard to replace as he or she knows the company's operations, strengths and weaknesses; thus, we expect a negative relationship between CEO EXP and performance change after the CEO change. We expect the BOARD EXP variable to be positively related as an experienced board also has valuable insight into the firm, thus, the amount of lost knowledge is reduced, and the new CEO can benefit from it. However, in the non-CEO regression we expect the opposite signs for both variables with the same arguments (i.e., CEO EXP with a positive and BOARD EXP with a negative sign).

Furthermore, we investigate the difference between routine and nonroutine CEO turnover. In a routine turnover, the former CEO retains a seat on the supervisory board.

⁹⁹ Analyzing efficiency values, for example, Luhnén (2009) finds that size and leverage are positively related to efficiency. Therefore, the results from efficiency analysis cannot be used one-to-one in our investigation. Thus, we only discuss the results from He et al. (2011).

Therefore, for the new CEO it could be difficult to change a company's operations, thus we do not expect any impact on performance after a routine turnover.

In Table 17 we present the summary statistics for the dependent and independent variables for both regression analyses. We check for multicollinearity (by calculating the variance inflation factor) and find no severe correlation between our variables for both regression analyses (see Appendix A Tables A.1–A.5).

Our sample shows a higher overall CEO change rate than that reported in Cheng et al. (2017), who report a rate of 6.53 percent, but one that is lower than the one reported by He et al. (2011), whose sample shows a change rate of 15 percent. We classify 25 percent of all changes as routine changes; He et al. (2011) report 33 percent and Cheng et al. (2017) report 58 percent. As all studies use a similar identification of routine turnover, it seems that it is less frequent for German CEOs to sit on a supervisory board after their dismissal from the management board.

Table 17. Summary statistics of dependent and independent variables

<i>Variable</i>	<i>Mean</i>	<i>St. Dev.</i>	<i>Min</i>	<i>Max</i>
TO CEO	0.10	0.31	0.00	1.00
TO CEO routine	0.02	0.15	0.00	1.00
TO CEO nonroutine	0.08	0.28	0.00	1.00
TO non-CEO	0.24	0.42	0.00	1.00
TO non-CEO one third rule	0.10	0.30	0.00	1.00
$CE_{t-1,t}$	1.03	0.24	0.54	1.95
$CE_{t-1,t+1}$	1.05	0.29	0.52	2.14
$CE_{t-1,t+2}$	1.07	0.35	0.47	2.46
$CE_{t-1,t+3}$	1.09	0.40	0.43	2.62
$RE_{t-1,t}$	1.02	0.19	0.56	1.81
$RE_{t-1,t+1}$	1.04	0.25	0.50	2.12
$RE_{t-1,t+2}$	1.04	0.27	0.50	2.18
$RE_{t-1,t+3}$	1.05	0.30	0.50	2.33
Relative ROE	0.13	0.28	-1.03	1.00
DIV	0.60	0.34	0.11	1.00
LEV	0.54	0.19	0.02	0.83
SIZE	18.38	1.98	13.46	24.21
REI	0.30	0.22	-0.01	0.86
OWN	0.27	0.44	0.00	1.00
CEO EXP	6.96	5.68	1.00	38.00
BOARD EXP	6.41	4.51	0.00	63.00

Note: To exclude extreme values, we winsorize leverage (LEV), reinsurance use (REI), the efficiency changes and the relative ROE to the 1% and 99% percentile. Because of the calculation of the efficiency value changes the sample size is reduced.

5 Empirical results

5.1 Impact of firm performance on executive board changes

5.1.1 Impact of firm performance on CEO change

In Table 18 we report the probit regression results for all CEO turnovers in our sample. Using $CE_{t-2,t-1}^S$ (columns 1 and 2) as a performance measure, we find a significant negative relationship between firm performance and the CEO turnover (i.e., insurers that

experience a decrease in cost efficiency are more likely to change their CEO). We obtain similar results when using $RE_{t-2,t-1}^S$ as a measure of an insurer's performance. However, the values are insignificant (p-value of 0.1037 column 3).¹⁰⁰ Moreover, in our robustness measure of firm performance, we find a significant inverse relationship between relative ROE and CEO turnover.

We obtain similar results for nonroutine CEO turnovers (see Table 19). The coefficients of the efficiency values become more negative and the coefficient of revenue efficiency is now significant. Furthermore, we find no significant negative relationship between firm performance and routine CEO turnover (see Table 20). Our results are in line with those of He and Sommer (2011) and Cheng et al. (2017), who use ROA as their performance measure.¹⁰¹ In summary, our findings support our hypothesis 1 that firm performance is inversely related to the probability of CEO change.

The coefficients of the line-of-business Herfindahl index (DIV), which we use as a measure of business complexity, are positive but not significant for overall and nonroutine turnovers. Therefore, the sign of our coefficients is in line with Parrino's (1997) argument that firms with less complex business are more likely to change their CEOs, because the replacement costs are lower. The DIV coefficients in He and Sommer (2011) and Cheng et al. (2017) are also positive, but their results are significant in the nonroutine regression analysis. Furthermore, the negative coefficients in the routine turnover regression are not significant but remain consistent with the reported results in He and Sommer (2011) and Cheng et al. (2017).

We find a positive significant relationship between firm size (SIZE) and overall, routine and nonroutine turnover. Thus, our results contradict the findings from Blackwell et al. (1994) but are consistent with He and Sommer (2011). As larger firms have potentially larger supervisory boards, our results may be interpreted in the way that larger supervisory boards are more effective at monitoring the CEOs work. The leverage (LEV) does not seem to play a significant role in turnover decisions. Cheng et al. (2017) find no significant relationship between leverage and turnover. However, we do find a significant negative correlation for nonroutine turnovers.

We cannot confirm the results of He and Sommer (2011) that reinsurance usage (REI) is significantly related to CEO turnover.

¹⁰⁰ In a robustness check, we winsorize leverage (LEV), reinsurance use (REI), the efficiency changes and the relative ROE to the 5% and 95% percentile. Using these values, the coefficients for the revenue efficiency changes become significant (in the overall and nonroutine turnover regressions). In contrary, the coefficient of the relative ROE is less significant. Other coefficients do not change as much in magnitude and significance.

¹⁰¹ We present the results for the absolute ROE, the absolute and relative return on assets (ROA) in Appendix B. Using ROA as performance measure, the results are only significant in the model with the interaction term $OWN \times ROA / \text{rel. ROA}$. However, the sign of the coefficients is negative in all cases.

The mutual dummy (OWN) is negatively significant for almost every regression. The only exceptions are columns 4, 10 and 16 where we interact $RE_{t-2,t-1}^s$ with the mutual dummy variable. Our results support the findings from He and Sommer (2011) and Cheng et al. (2017) that mutuals have lower turnover rates than stock insurers, independently of routine or nonroutine turnovers.

We find significant evidence that CEO turnover for mutual insurers is less sensitive to firm performance only in the overall turnover regression, when using cost efficiency as our performance measure (see column 2 in Table 18). These results are not confirmed when we use revenue efficiency and relative ROE as performance measures. Cheng et al. (2017) report a positive but insignificant relationship and He and Sommer (2011) find only a significant positive relationship when using the underwriting ROA.

Table 18. Probit regression results on CEO turnover

<i>all</i>	<i>TO CEO</i> (1)	<i>TO CEO</i> (2)	<i>TO CEO</i> (3)	<i>TO CEO</i> (4)	<i>TO CEO</i> (5)	<i>TO CEO</i> (6)
Intercept	-1.920*** (0.309)	-1.842*** (0.313)	-1.854*** (0.311)	-1.864*** (0.317)	-2.097*** (0.288)	-2.100*** (0.288)
$CE_{t-2,t-1}$	-0.152* (0.091)	-0.232** (0.101)				
$RE_{t-2,t-1}$			-0.197 (0.121)	-0.187 (0.132)		
Relative ROE_{t-1}					-0.183** (0.084)	-0.198** (0.087)
DIV	0.052 (0.074)	0.054 (0.074)	0.051 (0.074)	0.051 (0.074)	0.048 (0.073)	0.048 (0.073)
LEV	-0.154 (0.139)	-0.154 (0.139)	-0.158 (0.139)	-0.158 (0.139)	-0.179 (0.135)	-0.180 (0.135)
SIZE	0.049*** (0.014)	0.049*** (0.014)	0.048*** (0.014)	0.048*** (0.014)	0.052*** (0.014)	0.052*** (0.014)
REI	0.065 (0.112)	0.062 (0.112)	0.060 (0.112)	0.060 (0.112)	0.007 (0.108)	0.006 (0.109)
OWN	-0.261*** (0.054)	-0.732*** (0.256)	-0.263*** (0.054)	-0.207 (0.331)	-0.274*** (0.053)	-0.293*** (0.064)
BOARD EXP	-0.029*** (0.005)	-0.030*** (0.005)	-0.030*** (0.005)	-0.030*** (0.005)	-0.030*** (0.005)	-0.030*** (0.005)
CEO EXP	0.031*** (0.004)	0.031*** (0.004)	0.031*** (0.004)	0.031*** (0.004)	0.032*** (0.004)	0.032*** (0.004)
$OWN \times CE_{t-2,t-1}$		0.459* (0.243)				
$OWN \times RE_{t-2,t-1}$				-0.056 (0.326)		
$OWN \times rel. ROE_{t-1}$						0.158 (0.291)
Sample size	6,328	6,328	6,328	6,328	6,685	6,685

Note: ***, **, and * represent significance at the 1 percent, 5 percent, and 10 percent levels, respectively. The numbers in parentheses are the robust two-ways clustered standard errors. We apply probit regression and winsorize leverage (LEV), reinsurance use (REI), the efficiency changes and the relative ROE to the 1% and 99% percentile.

Finally, we discover a significant negative relationship between board tenure (BOARD EXP) and CEO turnover in all our analysis. Thus, we cannot confirm our assumption that CEOs may be more easily replaced in firms with more experienced boards. One

explanation could be that more experienced boards are hesitant to replace their CEO because they are afraid of losing their job under a new CEO. With their experience it may be hard to find a satisfactory new post. For example, Fee and Hadlock (2004) show that when managers lose their position and find a new one, the new position is significantly inferior. As expected, the CEO experience correlates significantly positively with CEO turnover.

Table 19. Probit regression results on nonroutine CEO turnover

<i>nonroutine</i>	<i>TO CEO</i> (7)	<i>TO CEO</i> (8)	<i>TO CEO</i> (9)	<i>TO CEO</i> (10)	<i>TO CEO</i> (11)	<i>TO CEO</i> (12)
Intercept	-1.879*** (0.328)	-1.807*** (0.330)	-1.815*** (0.328)	-1.850*** (0.336)	-2.062*** (0.302)	-2.068*** (0.302)
$CE_{t-2,t-1}$	-0.179* (0.097)	-0.248** (0.108)				
$RE_{t-2,t-1}$			-0.218* (0.131)	-0.187 (0.144)		
Relative ROE_{t-1}					-0.151* (0.091)	-0.178* (0.095)
DIV	0.109 (0.078)	0.110 (0.078)	0.107 (0.078)	0.107 (0.078)	0.099 (0.077)	0.099 (0.077)
LEV	-0.009 (0.147)	-0.008 (0.147)	-0.011 (0.148)	-0.011 (0.148)	-0.050 (0.143)	-0.052 (0.143)
SIZE	0.035** (0.015)	0.035** (0.015)	0.034** (0.015)	0.034** (0.015)	0.038** (0.015)	0.039*** (0.015)
REI	0.079 (0.118)	0.076 (0.118)	0.073 (0.117)	0.073 (0.117)	0.027 (0.114)	0.025 (0.114)
OWN	-0.173*** (0.056)	-0.563** (0.266)	-0.175*** (0.056)	0.006 (0.343)	-0.186*** (0.055)	-0.219*** (0.068)
BOARD EXP	-0.027*** (0.006)	-0.027*** (0.006)	-0.027*** (0.006)	-0.027*** (0.006)	-0.027*** (0.006)	-0.028*** (0.006)
CEO EXP	0.023*** (0.004)	0.023*** (0.004)	0.023*** (0.004)	0.023*** (0.004)	0.024*** (0.004)	0.025*** (0.004)
$OWN \times CE_{t-2,t-1}$		0.382 (0.253)				
$OWN \times RE_{t-2,t-1}$				-0.181 (0.337)		
$OWN \times \text{rel. } ROE_{t-1}$						0.272 (0.309)
Sample size	6,328	6,328	6,328	6,328	6,685	6,685

Note: ***, **, and * represent significance at the 1 percent, 5 percent, and 10 percent levels, respectively. The numbers in parentheses are the robust two-ways clustered standard errors. We apply probit regression and winsorize leverage (LEV), reinsurance use (REI), the efficiency changes and the relative ROE to the 1% and 99% percentile.

Table 20. Probit regression results on routine CEO turnover

<i>routine</i>	<i>TO CEO</i> (13)	<i>TO CEO</i> (14)	<i>TO CEO</i> (15)	<i>TO CEO</i> (16)	<i>TO CEO</i> (17)	<i>TO CEO</i> (18)
Intercept	-2.962*** (0.535)	-2.908*** (0.548)	-2.917*** (0.543)	-2.845*** (0.547)	-3.045*** (0.518)	-3.045*** (0.518)
$CE_{t-2,t-1}$	0.002 (0.156)	-0.080 (0.168)				
$RE_{t-2,t-1}$			-0.035 (0.192)	-0.106 (0.204)		
Relative ROE_{t-1}					-0.199 (0.131)	-0.166 (0.136)
DIV	-0.140 (0.129)	-0.134 (0.129)	-0.141 (0.129)	-0.141 (0.129)	-0.128 (0.127)	-0.129 (0.127)
LEV	-0.543** (0.232)	-0.549** (0.232)	-0.543** (0.233)	-0.550** (0.234)	-0.516** (0.226)	-0.516** (0.226)
SIZE	0.069*** (0.024)	0.071*** (0.024)	0.069*** (0.024)	0.069*** (0.025)	0.073*** (0.025)	0.073*** (0.025)
REI	0.006 (0.196)	0.001 (0.196)	0.005 (0.196)	0.001 (0.196)	-0.050 (0.194)	-0.047 (0.194)
OWN	-0.422*** (0.102)	-1.066** (0.495)	-0.423*** (0.102)	-0.967 (0.633)	-0.438*** (0.102)	-0.395*** (0.108)
BOARD EXP	-0.023*** (0.007)	-0.023*** (0.007)	-0.023*** (0.007)	-0.023*** (0.007)	-0.022*** (0.007)	-0.022*** (0.007)
CEO EXP	0.037*** (0.005)	0.038*** (0.005)	0.037*** (0.005)	0.038*** (0.005)	0.039*** (0.005)	0.039*** (0.005)
$OWN \times CE_{t-2,t-1}$		0.615 (0.462)				
$OWN \times RE_{t-2,t-1}$				0.533 (0.613)		
$OWN \times \text{rel. ROE}_{t-1}$						-0.455 (0.409)
Sample size	6,328	6,328	6,328	6,328	6,685	6,685

Note: ***, **, and * represent significance at the 1 percent, 5 percent, and 10 percent levels, respectively. The numbers in parentheses are the robust two-ways clustered standard errors. We apply probit regression and winsorize leverage (LEV), reinsurance use (REI), the efficiency changes and the relative ROE to the 1% and 99% percentile.

5.1.2 Impact of firm performance on non-CEO change

Table 21 presents the probit regression results for the non-CEO turnovers in our sample. The non-CEO turnover dummy variable is equal to 1 if at least one third of non-CEOs leave the management board.¹⁰² Using the efficiency values as our measure of firm performance, we cannot confirm hypothesis 2. Thus, it seems that the efficiency values are rather a noisier signal for the evaluation of non-CEOs and are not used to evaluate the capabilities of non-CEOs. However, using our robustness measure of relative ROE, we find a significant negative relationship between relative ROE and non-CEO turnover. This may suggest that the supervisory board focuses more on traditional accounting

¹⁰² Our results do not change significantly if we use one half or one quarter instead of one third of non-CEOs leaving the management board. The dummy variable indicating that we have changes of non-CEOs is more often equal to one if we set the boundary to one quarter. In this scenario, the sign of the size coefficient changes. However, this could be due to the fact the larger firms have larger management boards and thus experience more non-CEO changes (our initial reason to use the one third rule).

measures instead of looking at the whole production process when evaluating non-CEOs work.

Table 21. Probit regression results on non-CEO turnover

	<i>TO non-CEO</i> (19)	<i>TO non-CEO</i> (20)	<i>TO non-CEO</i> (21)	<i>TO non-CEO</i> (22)	<i>TO non-CEO</i> (23)	<i>TO non-CEO</i> (24)
Intercept	-0.902*** (0.310)	-0.935*** (0.312)	-1.067*** (0.321)	-1.000*** (0.324)	-0.985*** (0.284)	-0.986*** (0.284)
$CE_{t-2,t-1}$	0.084 (0.092)	0.113 (0.100)				
$RE_{t-2,t-1}$			0.212* (0.117)	0.151 (0.128)		
Relative ROE_{t-1}					-0.184** (0.085)	-0.192** (0.090)
DIV	-0.018 (0.075)	-0.018 (0.075)	-0.017 (0.075)	-0.017 (0.075)	-0.013 (0.073)	-0.013 (0.073)
LEV	0.140 (0.137)	0.140 (0.137)	0.137 (0.137)	0.136 (0.137)	0.163 (0.132)	0.163 (0.132)
SIZE	-0.026* (0.014)	-0.026* (0.014)	-0.024* (0.014)	-0.024* (0.014)	-0.017 (0.014)	-0.017 (0.014)
REI	0.067 (0.112)	0.068 (0.112)	0.069 (0.112)	0.067 (0.112)	0.045 (0.108)	0.045 (0.108)
OWN	-0.151*** (0.051)	0.020 (0.263)	-0.150*** (0.051)	-0.477 (0.334)	-0.148*** (0.050)	-0.157*** (0.059)
BOARD EXP	0.010* (0.005)	0.010* (0.005)	0.010* (0.005)	0.010* (0.005)	0.010** (0.005)	0.010** (0.005)
CEO EXP	-0.011** (0.004)	-0.011** (0.004)	-0.011** (0.004)	-0.011** (0.004)	-0.010** (0.004)	-0.010** (0.004)
$OWN \times CE_{t-2,t-1}$		-0.167 (0.252)				
$OWN \times RE_{t-2,t-1}$				0.320 (0.321)		
$OWN \times \text{rel. ROE}_{t-1}$						0.076 (0.263)
Sample size	6,328	6,328	6,328	6,328	6,685	6,685

Note: ***, **, and * represent significance at the 1 percent, 5 percent, and 10 percent levels, respectively. The numbers in parentheses are the robust two-ways clustered standard errors. The TO non-CEO dummy variable is defined as equal to 1 for year t if at least one third of the members of the management board (except the CEO) leaves the firm. We apply probit regression and winsorize leverage (LEV), reinsurance use (REI), the efficiency changes and the relative ROE to the 1% and 99% percentile.¹⁰³

We find a negative significant relationship between firm size (SIZE) and non-CEO turnover in our efficiency analyses. The results are in line with the idea that non-CEOs are not that easily changed in more complex/larger firms. Thus, the results are opposite to our findings in the CEO turnover regression, but they are in line with the findings from Blackwell et al. (1994), who investigate bank subsidiary managers.

The mutual dummy (OWN) variable is negative and significant in the analyses without the efficiency interaction terms. Similar to the CEO turnover analysis, our results suggest that monitoring in mutuals is less effective, thus, the turnover rates for non-CEOs are lower compared to stock insurers. Furthermore, these differences could be

¹⁰³ The impact of our independent variables does not change if we winsorize at the 5% and 95% percentile.

also explained by different hiring capabilities of new managers. Stock insurers may have it easier (e.g., due to a stronger brand or better performance incentives) to find potential candidates.

We also discover a significant negative relationship between CEO experience and non-CEO turnover. Similar to the earlier explanation, changing the board might rise also questions about the CEOs capabilities. Moreover, changes sometimes come at a risk that the CEO does not get along with new managers, thus it might be easier for him to support the management team. As high BOARD EXP is also indicative for the average age of the board, the significant positive result for BOARD EXP has been expected.

5.2 Firm performance after management turnover

5.2.1 Firm performance after CEO turnover

Table 22 presents the linear regression results on cost and revenue efficiency changes for the three time windows $(t - 1, t + 1)$, $(t - 1, t + 2)$, and $(t - 1, t + 3)$. The CEO change seems to have only a positive significant impact in the short-term $(t - 1, t + 1)$ cost efficiency development. For other time periods the impact is also positive but not significant. We cannot confirm the results from He et al. (2011) for revenue efficiency changes. It seems that changing the CEO does not affect revenue efficiency changes at all. Our results become stronger for nonroutine CEO turnovers (Table 23), again, only the impact on the short-term cost efficiency change is significant. As expected, we do not find an impact of routine turnover on performance (see Table 24). In addition, He et al. (2011) do not find a significant relationship between routine turnover and performance change. They contend that routine turnovers are not disciplinary and thus performance improvements cannot be expected. Moreover, as we have argued before, it could also be hard for the new CEO to effect change if the old CEO sits on the supervisory board. In conclusion, hypothesis 3 holds true only for short-term changes in cost efficiency.

We can confirm the results from He et al. (2011) that size (SIZE) and the mutual dummy (OWN) have a significant negative impact. For leverage (LEV) we find a significant negative relationship in the regression analyses on revenue efficiency and a positive impact on cost efficiency. Moreover, since we do not find an impact of diversification (DIV) on performance after CEO change, we cannot confirm the positive impact of the line-of-business Herfindahl index found by He et al. (2011). Surprisingly, the tenure of the departing CEO (CEO EXP) does not seem to have an impact, but the tenure of the board (BOARD EXP) is significantly negative related to efficiency changes for most of our analyses. This is the opposite of our expectations. The new CEO seems not to benefit from an experienced board. One reason could be that an experienced board is more

resilient in the adaption of new processes and thus performance improvements could be harder to achieve.

Table 22. OLS regression results on efficiency change
from $t - 1$ to $t + 1$ ($t + 2$ or $t + 3$)

	$CE_{t-1,t+1}$ (25)	$RE_{t-1,t+1}$ (26)	$CE_{t-1,t+2}$ (27)	$RE_{t-1,t+2}$ (28)	$CE_{t-1,t+3}$ (29)	$RE_{t-1,t+3}$ (30)
Intercept	1.129*** (0.041)	1.339*** (0.039)	1.167*** (0.050)	1.441*** (0.044)	1.278*** (0.057)	1.484*** (0.049)
TO CEO	0.018* (0.010)	0.000 (0.010)	0.010 (0.012)	0.002 (0.011)	0.019 (0.014)	0.013 (0.012)
DIV	0.006 (0.010)	-0.007 (0.010)	0.014 (0.013)	-0.007 (0.011)	0.016 (0.014)	-0.008 (0.012)
LEV	0.020 (0.019)	-0.059*** (0.018)	0.030 (0.024)	-0.097*** (0.021)	0.057** (0.027)	-0.137*** (0.023)
SIZE	-0.008*** (0.002)	-0.011*** (0.002)	-0.010*** (0.002)	-0.012*** (0.002)	-0.013*** (0.003)	-0.012*** (0.002)
OWN	-0.032*** (0.007)	-0.034*** (0.007)	-0.052*** (0.009)	-0.047*** (0.008)	-0.072*** (0.010)	-0.063*** (0.008)
CEO EXP	-0.001 (0.001)	-0.001 (0.001)	-0.001 (0.001)	-0.001 (0.001)	-0.001 (0.001)	-0.001 (0.001)
BOARD EXP	0.000 (0.001)	-0.002*** (0.001)	-0.001 (0.001)	-0.002*** (0.001)	-0.002* (0.001)	-0.004*** (0.001)
Year fixed effect	YES	YES	YES	YES	YES	YES
Sample size	6,320	6,320	5,973	5,973	5,649	5,649

Note: ***, **, and * represent significance at the 1 percent, 5 percent, and 10 percent levels, respectively. The numbers in parentheses are standard errors. We apply linear regression and winsorize leverage (LEV) and the efficiency changes to the 1% and 99% percentile.

Table 23. OLS regression results on efficiency change for nonroutine turnover
from $t - 1$ to $t + 1$ ($t + 2$ or $t + 3$)

	$CE_{t-1,t+1}$ (31)	$RE_{t-1,t+1}$ (32)	$CE_{t-1,t+2}$ (33)	$RE_{t-1,t+2}$ (35)	$CE_{t-1,t+3}$ (34)	$RE_{t-1,t+3}$ (36)
Intercept	1.129*** (0.041)	1.340*** (0.039)	1.167*** (0.050)	1.441*** (0.044)	1.277*** (0.057)	1.484*** (0.049)
TO CEO nonroutine	0.024** (0.011)	0.003 (0.011)	0.014 (0.014)	0.006 (0.012)	0.022 (0.016)	0.013 (0.014)
DIV	0.006 (0.010)	-0.007 (0.010)	0.014 (0.013)	-0.007 (0.011)	0.016 (0.014)	-0.008 (0.012)
LEV	0.020 (0.019)	-0.059*** (0.018)	0.030 (0.024)	-0.097*** (0.021)	0.057** (0.027)	-0.138*** (0.023)
SIZE	-0.008*** (0.002)	-0.011*** (0.002)	-0.010*** (0.002)	-0.012*** (0.002)	-0.013*** (0.003)	-0.012*** (0.002)
OWN	-0.032*** (0.007)	-0.034*** (0.007)	-0.052*** (0.009)	-0.047*** (0.008)	-0.072*** (0.010)	-0.063*** (0.008)
CEO EXP	-0.001 (0.001)	-0.001 (0.001)	-0.001 (0.001)	-0.001 (0.001)	-0.001 (0.001)	-0.001 (0.001)
BOARD EXP	0.000 (0.001)	-0.002*** (0.001)	-0.001 (0.001)	-0.002*** (0.001)	-0.002* (0.001)	-0.004*** (0.001)
YEAR FE	YES	YES	YES	YES	YES	YES
Sample size	6,320	6,320	5,973	5,973	5,649	5,649

Note: ***, **, and * represent significance at the 1 percent, 5 percent, and 10 percent levels, respectively. The numbers in parentheses are standard errors. We apply linear regression and winsorize leverage (LEV) and the efficiency changes to the 1% and 99% percentile.

Table 24. OLS regression results on efficiency change for routine turnover
from $t - 1$ to $t + 1$ ($t + 2$ or $t + 3$)

	$CE_{t-1,t+1}$ (37)	$RE_{t-1,t+1}$ (38)	$CE_{t-1,t+2}$ (39)	$RE_{t-1,t+2}$ (40)	$CE_{t-1,t+3}$ (41)	$RE_{t-1,t+3}$ (42)
Intercept	1.127*** (0.041)	1.339*** (0.039)	1.166*** (0.050)	1.441*** (0.044)	1.277*** (0.057)	1.483*** (0.049)
TO CEO routine	-0.006 (0.021)	-0.009 (0.019)	-0.007 (0.025)	-0.012 (0.022)	0.002 (0.029)	0.009 (0.025)
DIV	0.006 (0.010)	-0.007 (0.010)	0.014 (0.013)	-0.007 (0.011)	0.017 (0.014)	-0.008 (0.012)
LEV	0.020 (0.019)	-0.059*** (0.018)	0.030 (0.024)	-0.097*** (0.021)	0.056** (0.027)	-0.138*** (0.023)
SIZE	-0.008*** (0.002)	-0.011*** (0.002)	-0.010*** (0.002)	-0.012*** (0.002)	-0.012*** (0.003)	-0.012*** (0.002)
OWN	-0.033*** (0.007)	-0.034*** (0.007)	-0.053*** (0.009)	-0.048*** (0.008)	-0.072*** (0.010)	-0.064*** (0.008)
CEO EXP	-0.001 (0.001)	-0.001 (0.001)	-0.001 (0.001)	-0.001 (0.001)	-0.001 (0.001)	-0.001 (0.001)
BOARD EXP	-0.001 (0.001)	-0.002*** (0.001)	-0.001 (0.001)	-0.002*** (0.001)	-0.002** (0.001)	-0.004*** (0.001)
YEAR FE	YES	YES	YES	YES	YES	YES
Sample size	6,320	6,320	5,973	5,973	5,649	5,649

Note: ***, **, and * represent significance at the 1 percent, 5 percent, and 10 percent levels, respectively. The numbers in parentheses are standard errors. We apply linear regression and winsorize leverage (LEV) and the efficiency changes to the 1% and 99% percentile.

5.2.2 Firm performance after non-CEO turnover

To test hypothesis 4, we define a change in the management board as when the number of new managers is the same as the number of managers leaving the insurer. It turns out that the departure of managers from the board has a negative impact on firm efficiency (Table 25). However, it is only significant for cost efficiency in the mid- and long-term. An explanation for our findings could be that non-CEOs cannot adequately be replaced by their successors. Their change reduces experience and knowledge in the management team, which has a negative impact on insurers efficiency.

Our outcomes contradict the findings from Furtado and Rozeff (1987), who find a small performance increase after non-CEOs have left. Our results are also not in line with Mian (2001), who finds no significant impact on firm performance after non-CEO change. However, Furtado and Rozeff (1987) focus on the four top executives in the board of directors and Mian (2001) investigates CFO change. Furthermore, both studies use stock prices as measures for firm performance. Therefore, their results cannot be compared to our findings.

The impact of the control variables is comparable to the prior analysis of CEO change on firm performance. We find that size (SIZE) and the mutual dummy (OWN) have a significant negative impact. Leverage (LEV) has only a negative significant impact on revenue efficiency and a positive impact on cost efficiency. In line with our expectation, board tenure (BOARD EXP) has a significant negative impact on efficiency changes.

This may indicate that the management board loses know how, which has a negative impact on efficiency.

Table 25. OLS regression results on efficiency change for non-CEO change
from $t - 1$ to $t + 1$ ($t + 2$ or $t + 3$)

	$CE_{t-1,t+1}$ (43)	$RE_{t-1,t+1}$ (44)	$CE_{t-1,t+2}$ (45)	$RE_{t-1,t+2}$ (46)	$CE_{t-1,t+3}$ (47)	$RE_{t-1,t+3}$ (48)
Intercept	1.130*** (0.041)	1.342*** (0.039)	1.171*** (0.050)	1.443*** (0.044)	1.282*** (0.057)	1.485*** (0.049)
TO non-CEO	-0.018 (0.014)	-0.020 (0.013)	-0.032* (0.017)	-0.013 (0.015)	-0.039* (0.020)	-0.014 (0.017)
DIV	0.007 (0.010)	-0.006 (0.010)	0.014 (0.013)	-0.007 (0.011)	0.017 (0.014)	-0.008 (0.012)
LEV	0.021 (0.019)	-0.058*** (0.018)	0.032 (0.024)	-0.096*** (0.021)	0.059** (0.027)	-0.137*** (0.023)
SIZE	-0.008*** (0.002)	-0.011*** (0.002)	-0.010*** (0.002)	-0.012*** (0.002)	-0.013*** (0.003)	-0.012*** (0.002)
OWN	-0.033*** (0.007)	-0.034*** (0.007)	-0.053*** (0.009)	-0.048*** (0.008)	-0.073*** (0.010)	-0.064*** (0.008)
CEO EXP	-0.001 (0.001)	-0.001 (0.001)	-0.001 (0.001)	-0.001 (0.001)	-0.001 (0.001)	-0.001 (0.001)
BOARD EXP	0.000 (0.001)	-0.002*** (0.001)	-0.001 (0.001)	-0.002*** (0.001)	-0.002* (0.001)	-0.004*** (0.001)
YEAR FE	YES	YES	YES	YES	YES	YES
Sample size	6,320	6,320	5,973	5,973	5,649	5,649

Note: ***, **, and * represent significance at the 1 percent, 5 percent, and 10 percent levels, respectively. The numbers in parentheses are the standard errors. The TO non-CEO dummy variable is defined as being equal to 1 for year t if at least one third of the members of the management board (except the CEO) leaves the firm and the number of new managers is equal to number of leaving managers. We winsorize leverage (LEV) and the efficiency changes to the 1% and 99% percentile.

6 Conclusion

A large body of literature investigates the relationship between firm performance and change of management. In line with agency theory and intact corporate governance mechanisms, many scholars find that underperforming firms are more likely to change their CEO (e.g., Coughlan & Schmidt, 1985; Warner et al., 1988; Puffer & Weintrop, 1991; Murphy & Zimmermann, 1993; Huson et al., 2001; Farrell & Whidbee, 2003). Whereas empirical literature is quite clear on this inverse relationship, empirical evidence on firm performance after a change of management is quite diverse (e.g., Reinganum, 1985; Warner et al., 1988; Hotchkiss, 1995; Denis & Denis, 1995; Huson et al., 2004). Most studies focus only on CEO changes. Evidence on changes of other members in the executive team is not provided, with some exceptions, for example, Blackwell et al. (1994), Mian (2001), and Fee and Hadlock (2004).

This paper extends and contributes to the literature by including the impact of firm performance on changes within the management board and vice versa. A contribution of this paper is the analysis of the influence of non-CEOs, because they should have a significant impact on the corporate value. Therefore, it is important to understand the internal control mechanisms regarding non-CEOs. For this purpose, we analyze the

management board composition for German p/c insurance companies from 1979 to 2015. We employ DEA to estimate insurers' efficiency changes, which we use as performance measure. Efficiency scores offer the advantage to reflect the whole production process. At the same time, they are harder to manipulate. Besides He et al. (2011), our paper is the second one using efficiency change as a measure of firm performance in the context of management change.

Our results support the inverse relationship between firm performance and CEO turnover. However, we do not find support that efficiency improves after CEO changes. We only find a significant positive short-term effect on cost efficiency changes. Our results are in line with those of Reinganum (1985) and Warner et al. (1988), who find no significant performance reaction after CEO change. Our results suggest that CEOs of German p/c insurers are held responsible for weak firm performance, but new successors have limited influence on firm performance in the short term.

We find that decreasing efficiency scores cannot predict non-CEO changes. Only if we use the relative ROE, we find a significant negative relationship. This could suggest that the supervisory board focuses more on traditional accounting measures instead of looking at the whole production process when evaluating non-CEOs. After non-CEOs leave, we find that firm performance decreases. Their loss seems to lessen the experience and knowledge in the management team, which has an adverse impact on firm value.

Our findings have implications for insurance managers and policymakers. We show that CEOs are held responsible for poor firm performance. However, their change does not have a significant positive impact on firm performance afterwards. It seems that the poor performance may not have been solely the CEOs fault. Thus, other criteria should be used to evaluate CEOs' work. Regarding non-CEOs, it seems that they are laid off because of bad firm performance in terms of classical accounting measures. The whole production process is not evaluated. In consequence, efficiency decreases after non-CEOs change due to the loss of experience and knowledge.

Future research could investigate the different roles in the management team and the role of the supervisory board. Some studies look at the role of outside board members, which could be transferred to German supervisory boards. Many studies differentiate between routine and nonroutine CEO changes. We think this could be expanded to the management board. However, as data sources in Germany are not as rich as U.S. data, this could be an intensive undertaking. Moreover, it could be interesting to analyze the management change in a cross-European sample.

References

- Barro, J. R., & Barro, R. J. (1990). Pay, performance, and turnover of bank CEOs. *Journal of Labor Economics*, 8(4), 448–481.
- Beatty, R. P., & Zajac, E. J. (1987). CEO change and firm performance in large corporations: succession effects and manager effects. *Strategic Management Journal*, 8(4), 305–317.
- Biener, C., & Eling, M. (2011). The performance of microinsurance programs: a data envelopment analysis. *Journal of Risk and Insurance*, 78(1), 83–115.
- Biener, C., Eling, M., & Wirfs, J. H. (2016). The determinants of efficiency and productivity in the Swiss insurance industry. *European Journal of Operational Research*, 248(2), 703–714.
- Blackwell, D., Brickley, J., & Weisbach, M. (1994). Accounting information and internal performance evaluation: evidence from Texas banks. *Journal of Accounting and Economics* 17(3), 331–358.
- Bonnier, K. A., & Bruner, R. F. (1989). An analysis of stock price reaction to management change in distressed firms. *Journal of Accounting and Economics*, 11(1), 95–106.
- Braun, A., Schmeiser, H., & Rymaszewski, P. (2015). Stock vs. mutual insurers: who should and who does charge more? *European Journal of Operational Research*, 242(3), 875–889.
- Charnes, A., Cooper, W. W., & Rhodes, E. (1978). Measuring the efficiency of decision making units. *European Journal of Operational Research*, 2(6), 429–444.
- Cheng, J., Cummins, J. D., & Lin, T. (2017). Organizational form, ownership structure, and CEO turnover: evidence from the property-casualty insurance industry. *Journal of Risk and Insurance*, 84(1), 95–126.
- Cheng, J., Elyasiani, E., & Jia, J. (2011). Institutional ownership stability and risk taking: evidence from the life-health insurance industry. *Journal of Risk and Insurance*, 78(3), 609–641.
- Cornelli, F., Kominek, Z., & Ljungqvist, A. (2013). Monitoring managers: does it matter? *Journal of Finance*, 68(2), 431–481.
- Coughlan, A. T., & Schmidt R. M. (1985). Executive compensation, management turnover, and firm performance: an empirical investigation. *Journal of Accounting and Economics*, 7(1–3), 44–66.
- Cummins, J. D., Rubio-Misas, M., & Zi, H. (2004). The effect of organizational structure on efficiency: evidence from the Spanish insurance industry. *Journal of Banking and Finance*, 28(12), 3113–3150.
- Cummins, J. D., & Weiss, M. A. (2013). Analyzing firm performance in the insurance industry using frontier efficiency and productivity methods. *Handbook of insurance* (pp. 795–861). New York: Springer.

- Cummins, J. D., & Xie, X. (2008). Mergers and acquisitions in the US property-liability insurance industry: productivity and efficiency effects. *Journal of Banking and Finance*, 32(1), 30–55.
- Denis, J. D., & Denis, D. K. (1995). Performance changes following top management dismissals. *Journal of Finance*, 50(4), 1029–1057.
- Eisfeldt, A. L., & Kuhnen, C. M. (2013). CEO turnover in a competitive assignment framework. *Journal of Financial Economics*, 109(2), 351–372.
- Eling, M., & Luhnen, M. (2010). Frontier efficiency methodologies to measure performance in the insurance industry: overview, systematization, and recent developments. *Geneva Papers on Risk and Insurance – Issues and Practice*, 35(2), 217–265.
- Eling, M., & Marek, S. (2014). Corporate governance and risk taking: evidence from the U.K. and German insurance markets. *Journal of Risk and Insurance*, 81(3), 653–682.
- Eling, M., & Schaper, P. (2017). Under pressure: how the business environment affects productivity and efficiency of European life insurance companies. *European Journal of Operational Research*, 258(3), 1082–1094.
- Farrell, M. J. (1957). The measurement of productive efficiency. *Journal of the Royal Statistical Society*, 120(3), 253–281.
- Farrell, K. A., & Whidbee, D. A. (2003). Impact of firm performance expectations on CEO turnover and replacement decisions. *Journal of Accounting and Economics*, 36(1–3), 165–196.
- Fee, C. E., & Hadlock, C. J. (2000). Management turnover and product market competition: empirical evidence from the U.S. newspaper industry. *Journal of Business*, 73(2), 205–243.
- Fee, C. E., & Hadlock, C. J. (2004). Management turnover across the corporate hierarchy. *Journal of Accounting and Economics*, 37(1), 3–38.
- Fich, E. M., & Shivadasani, A. (2006). Are busy boards effective monitors? *Journal of Finance*, 61(2), 689–724.
- Furtado, E. P. H., & Rozeff, M. S. (1987). The wealth effects of company initiated management changes. *Journal of Financial Economics*, 18(1), 147–160.
- Hazarika, S., Karpoff, J. M., & Nahata, R. (2012). Internal corporate governance, CEO turnover, and earnings management. *Journal of Financial Economics*, 104(1), 44–69.
- He, E., & Sommer D. W. (2011). CEO turnover and ownership structure: evidence from the U.S. property-liability insurance industry. *Journal of Risk and Insurance*, 78(3), 673–701.
- He, E., Sommer D. W., & Xie, X. (2011). The impact of CEO turnover on property-liability insurer performance. *Journal of Risk and Insurance*, 78(3), 583–608.
- Ho, C.-L., Lai, G. C., & Lee, J.-P. (2013). Organizational structure, board composition, and risk taking in the U.S. property casualty insurance industry. *Journal of Risk and Insurance*, 80(1), 169–203.

- Holmström, B. (1979). Moral hazard and observability. *Bell Journal of Economics*, 10(1), 74–91.
- Hotchkiss, E. S. (1995). Postbankruptcy performance and management turnover. *Journal of Finance*, 50(1), 3–21.
- Huson, M. R., Malatesta, P. H., & Parrino, R. (2004). Managerial succession and firm performance. *Journal of Financial Economics*, 74(2), 237–275.
- Huson, M. R., Parrino, R., & Starks, L. T. (2001). Internal monitoring mechanisms and CEO turnover: a long-term perspective. *Journal of Finance*, 56(6), 2265–2297.
- Jenter, D., & Kanaan, F. (2015). CEO turnover and relative performance evaluation. *Journal of Finance*, 70(5), 2155–2183.
- Kaffash, S., Azizi, R., Huang, Y., & Zhu, J. (2020). A survey of data envelopment analysis applications in the insurance industry 1993–2018. *European Journal of Operational Research*, 284(3), 801–813.
- Khanna, N., & Poulsen, A. B. (1995). Managers of financially distressed firms: villains or scapegoats? *Journal of Finance*, 50(3), 919–940.
- Leone, A. J., & Liu, M. (2010). Accounting irregularities and executive turnover in founder-managed firms. *Accounting Review*, 85(1), 287–314.
- Leverly, J. T., & Grace, M. F. (2012). Dupes or incompetents? An examination of management's impact on firm distress. *Journal of Risk and Insurance*, 79(3), 751–783.
- Li, F., & Srinivasan, S. (2011). Corporate governance when founders are directors. *Journal of Financial Economics*, 102(2), 454–469.
- Liebertson, S., & O'Connor, J. F. (1972). Leadership and organizational performance: a study of large corporations. *American Sociological Review*, 37(2), 117–130.
- Luhnen, M. (2009). Determinants of efficiency and productivity in German property-liability insurance: evidence for 1995–2006. *Geneva Papers on Risk and Insurance – Issues and Practice*, 34(3), 483–505.
- Mahlberg, B., & Url, T. (2010). Single market effects on productivity in the German insurance industry. *Journal of Banking and Finance*, 34(7), 1540–1548.
- Mian, S. (2001). On the choice and replacement of chief financial officers. *Journal of Financial Economics*, 60(1), 143–175.
- Morck, R., Shleifer, A., & Vishny, R. W. (1989). Alternative mechanisms for corporate control. *American Economic Review*, 79(4), 842–852.
- Murphy, K. J., & Zimmermann, J. L. (1993). Financial performance surrounding CEO turnover. *Journal of Accounting and Economics*, 16(1–3), 273–315.
- Parrino, R. (1997). CEO turnover and outside succession: a cross-sectional analysis. *Journal of Financial Economics*, 46, 165–197.
- Puffer, S. M., & Weintrop, J. B. (1991). Corporate performance and CEO turnover: the role of performance expectations. *Administrative Science Quarterly*, 36(1), 1–19.

- Reinganum, M. R. (1985). The effect of executive succession on stockholder wealth. *Administrative Science Quarterly*, 30(1), 46–60.
- Simar, L., & Wilson, P. W. (2007). Estimation and inference in two-stage, semi-parametric models of production processes. *Journal of Econometrics*, 136(1), 31–64.
- Warner, J. B., Watts, R. L., & Wruck, K. H. (1988). Stock prices and top management changes. *Journal of Financial Economics*, 20, 461–492.
- Weiner, N., & Mahoney, T. A. (1981). A model of corporate performance as a function of environmental, organizational, and leadership influences. *Academy of Management Journal*, 24(3), 453–470.
- Weisbach, M. S. (1988). Outside directors and CEO turnover. *Journal of Financial Economics*, 20, 431–460.

Appendix A: Correlation matrices

Table A.1. Pearson correlation and variance inflation factors (VIF) of regressors in the regression analysis of cost efficiency change on management change

	CE _{t-1,t}	DIV	LEV	SIZE	REI	OWN	CEO EXP	BOARD EXP	VIF
CE _{t-1,t}	1.00	0.02	-0.02	-0.04	0.02	-0.04	-0.01	-0.01	1.00
DIV		1.00	-0.15	-0.42	-0.16	-0.09	-0.01	-0.03	1.37
LEV			1.00	0.50	-0.28	-0.18	0.00	-0.02	1.45
SIZE				1.00	-0.24	-0.06	-0.05	0.02	1.70
REI					1.00	-0.04	0.04	-0.02	1.23
OWN						1.00	0.15	0.10	1.10
CEO EXP							1.00	0.32	1.15
BOARD EXP								1.00	1.12

Table A.2. Pearson correlation and variance inflation factors (VIF) of regressors in the regression analysis of revenue efficiency change on management change

	RE _{t-1,t}	DIV	LEV	SIZE	REI	OWN	CEO EXP	BOARD EXP	VIF
RE _{t-1,t}	1.00	0.03	-0.02	-0.08	0.01	-0.04	-0.03	-0.03	1.01
DIV		1.00	-0.15	-0.42	-0.16	-0.09	-0.01	-0.03	1.37
LEV			1.00	0.50	-0.28	-0.18	0.00	-0.02	1.45
SIZE				1.00	-0.24	-0.06	-0.05	0.02	1.70
REI					1.00	-0.04	0.04	-0.02	1.23
OWN						1.00	0.15	0.10	1.10
CEO EXP							1.00	0.32	1.15
BOARD EXP								1.00	1.13

Table A.3. Pearson correlation and variance inflation factors (VIF) of regressors in the regression analysis of relative ROE on management change

	Rel. ROE	DIV	LEV	SIZE	REI	OWN	CEO EXP	BOARD EXP	VIF
Rel. ROE	1.00	-0.02	0.16	0.21	-0.14	-0.03	0.05	0.08	1.01
DIV		1.00	-0.17	-0.43	-0.14	-0.10	-0.02	-0.05	1.37
LEV			1.00	0.51	-0.30	-0.16	0.02	0.00	1.45
SIZE				1.00	-0.25	-0.05	-0.03	0.04	1.70
REI					1.00	-0.05	0.02	-0.03	1.23
OWN						1.00	0.15	0.10	1.10
CEO EXP							1.00	0.33	1.15
BOARD EXP								1.00	1.13

Table A.4. Pearson correlation and variance inflation factors (VIF) of regressors
in the regression analysis of CEO change on performance

	TO CEO	DIV	LEV	SIZE	OWN	CEO EXP	BOARD EXP	VIF
TO CEO	1.00	-0.01	0.02	0.04	-0.06	0.08	-0.04	1.02
DIV		1.00	-0.16	-0.43	-0.10	-0.02	-0.05	1.26
LEV			1.00	0.51	-0.16	0.02	0.00	1.40
SIZE				1.00	-0.05	-0.03	0.04	1.64
OWN					1.00	0.15	0.10	1.07
CEO EXP						1.00	0.33	1.16
BOARD EXP							1.00	1.14

Note: We report the Pearson correlation and variance inflation factors for the lagged control variables diversification (DIV), leverage (LEV), size (SIZE), mutual indicator (OWN), CEO tenure (CEO EXP) and average board tenure (BOARD EXP).

Table A.5. Pearson correlation and variance inflation factors (VIF) of regressors
in the regression analysis of non-CEO change on performance

	TO CEO	DIV	LEV	SIZE	OWN	CEO EXP	BOARD EXP	VIF
TO non-CEO	1.00	0.00	0.01	-0.01	-0.04	-0.03	0.01	1.00
DIV		1.00	-0.16	-0.43	-0.10	-0.02	-0.05	1.26
LEV			1.00	0.51	-0.16	0.02	0.00	1.40
SIZE				1.00	-0.05	-0.03	0.04	1.64
OWN					1.00	0.15	0.10	1.07
CEO EXP						1.00	0.33	1.15
BOARD EXP							1.00	1.13

Note: We report the Pearson correlation and variance inflation factors for the lagged control variables diversification (DIV), leverage (LEV), size (SIZE), mutual indicator (OWN), CEO tenure (CEO EXP) and average board tenure (BOARD EXP).

Appendix B: ROE, ROA and relative ROA as performance measures

Table B.1. Probit regression results on CEO turnover using absolute ROE, absolute and relative ROA as performance measures.

	<i>TO CEO</i>	<i>TO CEO</i>	<i>TO CEO</i>	<i>TO CEO</i>	<i>TO CEO</i>	<i>TO CEO</i>
Intercept	-2.077*** (0.287)	-2.079*** (0.287)	-2.035*** (0.285)	-2.054*** (0.286)	-2.034*** (0.285)	-2.056*** (0.286)
ROE_{t-1}	-0.227 (0.147)	-0.247 (0.152)				
ROA_{t-1}			-0.725 (0.488)	-0.921* (0.501)		
Relative ROA_{t-1}					-0.097 (0.065)	-0.124* (0.066)
DIV	0.044 (0.073)	0.044 (0.073)	0.041 (0.073)	0.043 (0.073)	0.041 (0.073)	0.043 (0.073)
LEV	-0.183 (0.135)	-0.184 (0.135)	-0.197 (0.134)	-0.189 (0.134)	-0.198 (0.134)	-0.189 (0.134)
SIZE	0.051*** (0.014)	0.051*** (0.014)	0.049*** (0.014)	0.049*** (0.014)	0.049*** (0.014)	0.049*** (0.014)
REI	0.012 (0.108)	0.011 (0.109)	0.010 (0.109)	0.010 (0.109)	0.010 (0.109)	0.010 (0.109)
OWN	-0.274*** (0.053)	-0.290*** (0.065)	-0.270*** (0.053)	-0.307*** (0.067)	-0.269*** (0.053)	-0.310*** (0.067)
BOARD EXP	-0.030*** (0.005)	-0.030*** (0.005)	-0.030*** (0.005)	-0.030*** (0.005)	-0.030*** (0.005)	-0.030*** (0.005)
CEO EXP	0.032*** (0.004)	0.032*** (0.004)	0.032*** (0.004)	0.032*** (0.004)	0.032*** (0.004)	0.032*** (0.004)
OWN × ROE _{t-1}		0.256 (0.596)				
OWN × ROA _{t-1}				2.043 (2.077)		
OWN × rel. ROA _{t-1}						0.283 (0.274)
Sample size	6,685	6,685	6,685	6,685	6,685	6,685

Note: ***, **, and * represent significance at the 1 percent, 5 percent, and 10 percent levels, respectively. The numbers in parentheses are the robust two-ways clustered standard errors. We apply probit regression and winsorize leverage (LEV), reinsurance use (REI), the ROE, ROA and the relative ROA to the 1% and 99% percentile. The relative return on assets (ROA) is the insurer-specific ROA divided by the best overall ROA each year.

Table B.2. Probit regression results on non-CEO turnover using absolute ROE, absolute and relative ROA as performance measures.

	<i>TO non-CEO</i> (19)	<i>TO non-CEO</i> (20)	<i>TO non-CEO</i> (21)	<i>TO non-CEO</i> (22)	<i>TO non-CEO</i> (23)	<i>TO non-CEO</i> (24)
Intercept	-0.969*** (0.284)	-0.970*** (0.284)	-0.928*** (0.281)	-0.939*** (0.282)	-0.929*** (0.281)	-0.942*** (0.282)
ROE _{t-1}	-0.245* (0.148)	-0.256* (0.155)				
ROA _{t-1}			-0.814 (0.499)	-0.932* (0.526)		
Relative ROA _{t-1}					-0.113* (0.065)	-0.131* (0.069)
DIV	-0.017 (0.073)	-0.017 (0.073)	-0.020 (0.073)	-0.019 (0.073)	-0.020 (0.073)	-0.019 (0.073)
LEV	0.159 (0.132)	0.159 (0.132)	0.145 (0.132)	0.149 (0.132)	0.144 (0.131)	0.149 (0.132)
SIZE	-0.018 (0.014)	-0.018 (0.014)	-0.020 (0.014)	-0.020 (0.014)	-0.020 (0.014)	-0.019 (0.014)
REI	0.048 (0.108)	0.048 (0.108)	0.047 (0.108)	0.046 (0.109)	0.046 (0.108)	0.045 (0.109)
OWN	-0.149*** (0.050)	-0.157*** (0.058)	-0.144*** (0.050)	-0.164*** (0.059)	-0.144*** (0.050)	-0.167*** (0.059)
BOARD EXP	0.010** (0.005)	0.010** (0.005)	0.010** (0.005)	0.010** (0.005)	0.010** (0.005)	0.010** (0.005)
CEO EXP	-0.010** (0.004)	-0.010** (0.004)	-0.010** (0.004)	-0.010** (0.004)	-0.010** (0.004)	-0.010** (0.004)
OWN × ROE _{t-1}		0.131 (0.496)				
OWN × ROA _{t-1}				1.116 (1.704)		
OWN × rel. ROA _{t-1}						0.166 (0.223)
Sample size	6,685	6,685	6,685	6,685	6,685	6,685

Note: ***, **, and * represent significance at the 1 percent, 5 percent, and 10 percent levels, respectively. The numbers in parentheses are the robust two-ways clustered standard errors. The TO non-CEO dummy variable is defined as equal to 1 for year t if at least one third of the members of the management board (except the CEO) leaves the firm. We apply probit regression and winsorize leverage (LEV), reinsurance use (REI), the ROE, ROA and the relative ROA to the 1% and 99% percentile. The relative return on assets (ROA) is the insurer-specific ROA divided by the best overall ROA each year.

Curriculum Vitae

Personal Information

Name: Martin Lehmann
Date of Birth: 10th January 1987
Place of Birth: Königs Wusterhausen (Germany)
Nationality: German

Education

08/2016 – 09/2020 **University of St. Gallen**, St. Gallen, Switzerland
Ph.D. in Finance

10/2010 – 07/2013 **University of Ulm**, Ulm, Germany
M.Sc. in Mathematics and Management

08/2011 – 12/2012 **San Diego State University**, San Diego, USA
M.Sc. in Applied Mathematics

10/2007 – 09/2010 **University of Ulm**, Ulm, Germany
B.Sc. in Mathematics and Management

Work Experience

08/2016 – 07/2020 **Institute of Insurance Economics (I.VW-HSG)**
Project manager and research assistant

04/2013 – 07/2016 **Kampmann, Berg & Partner**
Senior Consultant