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INFORMATION ET ASSURANCE : LA SEGMENTATION DES RISQUES ET LA PRÉVENTION DANS UN CONTEXTE DE DISPONIBILITÉ DES DONNÉES

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General introduction

This thesis aims at improving the understanding of the impact that new and massive data has on the insurance sector, while also examining the potential changes brought by the current development of digital technologies, and in particular by the information that becomes available as a consequence of this transformation.

The thesis focuses in particular on the changes related to risk classification and risk prevention, created by the availability of information and by the new data sources, which were not available before. Would the impact on the high and low risks' coverage be necessarily different? What are the possible consequences for the co-existence and the comparative benefits of mutual and stock insurance, given a technical possibility of an enhanced risk segmentation? Could prevention be improved through the new contract types? What types of policyholders could be interested in these new contracts? These are the questions that we aim to answer through the chapters of the present thesis while making use of different approaches and perspectives that we will present further in this introduction.

The questions that form our main point of interest in this work are brought to light by the current state of affairs in terms of technological development and the modern digital environment that we live in. Since the fast development of *Information and communications technology* (ICT) and the decrease in the cost of related devices during recent years, the access to these devices and their use have become more widespread. Speaking of internet connection alone, the share of EU-27 households with internet access had risen to 90% in 2019, which is 26 percentage points higher than in 2009 (European Commission, 2020b). Additionally, one of six European Commission priorities for the period 2019-2024 is *A Europe fit for the digital age* (European Commission, 2019).

As a consequence of ICT development, the data produced by various electronic devices can be collected continuously through smartphones, sensors, or connected boxes, and also transmitted and processed at a faster rate and a lower cost due to the increasing computing capacity. For instance, five billion internet searches are made and four terabytes[1] of data are created from each connected car in a day.[2] The European Commission communication states that 80% of the processing and analysis of data takes place in data centers and centralized computing facilities, and 20% in smart connected objects, such as cars, home appliances, or manufacturing robots, and these proportions are projected to be inverted by 2025 (European Commission, 2020a).

The quantity of available data is increasing with the number of connected devices and the number of connections made. Additionally, there is a qualitative change regarding the available data. New types of data have become accessible, arising from new sources such as online data from search engines and social media, or data from connected devices, such as smartphones, wearable devices, and sensors. The number of connected cars, which can send and receive information through the use of vehicle telematics, is estimated to be over one billion in use worldwide.[3] Hence, standard types of information are easier to collect, for instance through online declarations and surveys, and are cheaper to store and analyze, while new types of data become accessible, such as data on individual behavior.

New technologies, and specifically ICT, have a prominent impact on all the industries. But the sectors the most affected by the changes are those that rely predominantly on the use of data to run the business, given that new technologies bring the most profound transformation in relation to information collection and analysis. The insurance sector is an exceptionally good example of a market built around information and currently undergoing a transformation.

Insurers have always relied on data to assess individual risks. Traditional datasets used for the risk assessment are mostly built on the basis of direct declarative information provided by the policyholders. These datasets are easier to create and less costly to treat nowadays. Additionally, since new types of data become available, the insurers are increasingly using this new information to complement traditional datasets (EIOPA, 2019).

The dependence between the insurance functioning and the available information has one main consequence which constitutes an important subject of study in economic theory: the information asymmetry issues. The distribution of relevant information between two sides of the contracting arrangement, the insurer and the policyholder, determines in multiple ways the shape of insurance contracts, their price, and the insurance market structure.

[1] One terabyte is equal to 1000^4 bytes.
[2] "*How much data is generated each day?*", World Economic Forum, 2019.
[3] "*Connected cars worldwide*", Statista, 2020.

It is generally assumed that the distribution of relevant information, namely regarding the policyholders' risk types and actions, is shifted towards one side. The policyholders are assumed to have complete knowledge of their characteristics regarding the risk level, and of the actions that they are undertaking, or not, in relation to risk exposure. Those elements are simultaneously assumed to be hidden from the insurer, producing market inefficiencies known as adverse selection and moral hazard. Seminal discoveries of economic theoreticians describe the situations in which those issues arise and offer possible ways to correct the inefficiencies resulting from such a one-sided distribution of information (Akerlof, 1970; Rothschild and Stiglitz, 1978; Hölmstrom, 1979).

Information asymmetry has long remained a highly relevant hypothesis and recent research continues to provide important extensions on related issues (Picard, 2014; Mimra and Wambach, 2017; Picard, 2019). Nevertheless, given an increasing availability of information, it can be hard not to question the possibility of approaching the information *symmetry*. For instance, the discussions on personalization of insurance, increased risk classification, and behavior-based contracts show that the insurers are learning more about the policyholders' needs, characteristics and behavior, and these dynamics of changing relationship between insurers and policyholders bring a series of new questions.

In this context, this thesis aims to contribute to a better understanding of the ways in which new data could affect insurance functioning, from different points of view. We identify a series of possible issues, which are the impact on the information available on different risk types and different insurance forms, and the impact on prevention. Giving some elements of answer or providing some insights to these questions could contribute to the development of better products and services and foster the reflection on relevant tools and policies needed to assist and cultivate the ongoing digital transformation of the insurance sector.

This thesis addresses the announced objective from theoretical and experimental perspective beginning primarily with a thorough presentation of the context, which is done in Chapter 1.

In this first chapter, we aim at dressing a global picture and discussing how the fundamental aspects of the insurance business are modified with access to the new data. A primary discussion on the underlying situation is useful to grasp the nature of the following research questions and the issues and debates stemming from the given context. We provide concrete examples of new actors and new contracts and discuss the overall changes in the insurance market. It allows us to describe the setting that explains the focus of this thesis, which can be summed up by two main questions linked to risk classification and risk prevention.

The questions related to risk classification and its impact on different parties of insurance contracting are addressed in Chapters 2 and 3 through two theoretical models. These questions are motivated by potential consequences that the availability of information can have on the risk segmentation and personalization of insurance offers, which are expected from the insurers having increasing access to the information on individual risks.

In Chapter 2, we aim at showing that a private stock insurer would not strive to keep only low-risk policyholders, even if the information is symmetrical and the insurer can perfectly distinguish between different risk types. We provide a theoretical demonstration of the importance of high-risk policyholders and stress the point that attracting new low-risk agents by using the available data on risk types is as important as keeping the existent high risks. We, therefore, develop an argument regarding the idea that new data should be used to help the latter in decreasing their risk exposure when it is possible.

In Chapter 3, our theoretical analysis is motivated by the viewpoint related to the issue we address in Chapter 2, the idea being that the availability of information is only beneficial for private insurers and low-risk agents, since the former will offer lower premiums for the latter. In particular, we explore mutual insurance in our theoretical study and model explicitly the fact that mutuals may be less urged to use all the available information to classify and discriminate between risks, compared to the private stock insurers. We also introduce different mechanisms of managing insolvency, which is the second important aspect that makes mutual insurance distinct, compared to stock insurance. We examine specifically the conditions making mutual insurance more advantageous both for high-risk and low-risk agents, compared to the private insurer who applies more price discrimination. Our findings can contribute to the understanding of the coexistence between mutual and stock insurance, and to highlight that personalization is not necessarily desirable for the stock insurers, and the mutual insurance can be beneficial in the current context.

In Chapter 4, we use a theoretical and an experimental approach to study the new type of insurance contracts based on the prevention effort, which does not yet fully exist. These behavioral contracts could, in theory, help to promote prevention, and partial offers of such contracts are already used by insurers. We compare this behavioral contract to the classic experience-based system, such as a bonus-malus system, and examine the incentives provided by each, as well as the individual preferences towards one or the other of contract types. We find that the subjects insured through the behavioral contracts invest more in prevention effort and that the initial preferences for prevention seem to be an important determinant of the contract choice when both contract types are offered.

We will now introduce more specifically each of the research questions and approaches that constitute this work.

This thesis starts with the contextual analysis of the changes that currently shape the insurance sector (Chapter 1). We present a detailed overview of the changes that the insurance practice is undergoing, focusing on those that are relevant for the main subjects we are interested in, namely the personalization and risk classification and the use of behavioral data for risk prevention.

Our main contribution is to provide an understanding of the background from which these transformations originate, especially those that call for a reconsideration of some economic theory hypotheses and an examination of new eventualities. Thus, we aim at offering an appreciation of new tendencies and new challenges created by the actual context of data accessibility.

To analyze the current transformations in the sector, we first present the overview of the aspects of new data becoming available to the insurers. We present its characteristics, such as granularity and an unorganized nature, and we proceed by presenting new sources of information that are generated by new technologies. We also discuss new tools available for the analysis of more voluminous and unorganized data.

We proceed with the analysis of new possibilities available to the insurers, by illustrating them with concrete examples of new actors emerging in the market and new products being offered. We provide examples of companies integrating new data and new technologies in their business, with a particular focus on two big insurance sectors, health and automobile, given that they are the biggest branches aside from life insurance.

Finally, we provide an analysis of two main issues of interest, which are risk classification and risk prevention. We discuss how those two elements, historically important for insurance functioning, are changing in the current data-rich context. In particular, we examine how they are linked to the information asymmetry issues which are challenged today given the data availability. We also provide a discussion on various practical and societal questions emerging from those issues that can seem theoretical at first and provide a broader perspective for the questions that we address in the following chapters.

Our first theoretical study (Chapter 2) analyzes the hypothesis of information symmetry and related refined risk classification in relation to the high-risk agents. Our objective is to address a concern that arises from recent innovations in the insurance sector related to the agents who are revealed to be high risks. Since the insurer could, in theory, learn more about a policyholder's risk level and enhance risk classification by better differentiating between risk types, we consider whether the strategy of focusing only on the low-risk agents is expedient for the insurers. By this, we aim at contributing to the ongoing debate on the impact that data availability can have on high-risk agents in particular.

To examine this question, we present a one-period model of insurer's aggregate risk given a portfolio of independent high and low risks. We, therefore, focus on the stock insurance portfolio with regard to insolvency, and especially on the role of the high-risk policyholders. While the literature considers mostly homogeneous portfolios (Cummins, 1991; M. Smith and Kane, 1994; Gatzert and Schmeiser, 2012; Albrecht and Huggenberger, 2017), we contribute to the discussion by considering the heterogeneity and the interaction between the latter, the solvency constraints, and the finite portfolio size.

The rationale for considering this framework, and in particular the solvency issues and the finite portfolio size, is the following. On the one hand, European insurers have to control their probability of insolvency according to the legal terms of policyholders' protection (Solvency II). In particular, insurers have to provide a correct evaluation of their risk and to hold proper amounts of risk-bearing capital, which should be used to maintain the ruin probability under a required level of 0.5% a year. On the other hand, we find it important to consider finite portfolio size because it is relevant for the companies operating in specific branches where the number of policyholders is limited, and especially for the new insurance firms that enter the market.

We also introduce in our model two types of risk loading, additive loading and multiplicative loading. This is because an important aspect of managing the probability of insolvency is a buffer fund, which can be partially formed by the individual contributions through the risk loading (Cummins, 1974; Cummins, 1991; M. Smith and Kane, 1994). Thus, the presence of a risk loading allows reinforcing the risk-bearing capacity to keep the probability of insolvency under the required level.

We analyze the link between the size of the insurer's portfolio, its composition represented by the combination of heterogeneous risk types, and their contribution to the buffer fund through the loaded premiums, which are the elements that define the insurer's risk and solvency. We obtain our results first for binary distributed, and then for normally distributed risks and we show that high-risk agents contribute proportionally more to the buffer fund when the loading is multiplicative and the risks are binary distributed. Consequently, the pool can be smaller if it is heterogeneous or contains high risks only, compared to the homogeneous low-risk pool.

When risks are normally distributed, high-risk policyholders do not necessarily enable a faster decrease of the probability of insolvency, because the size of the loss can take an infinite number of values. However, even though we do not observe the same result as with a binary distribution, we point out that for a fixed level of probability of insolvency, the premium is still decreasing with the size of the pool, if the proportion of high-risk and low-risk agents is not affected. Additionally, the premium decreases with the risk level of high-risk agents.

Hence, we show that it is not necessarily desirable for the insurer to form a homogeneous pool of low-risk policyholders, at least from the regulatory perspective. Homogeneous pools that are sufficiently large might be difficult to create, in particular with regard to the increasingly strengthening equity constraints imposed by the regulators. Thus, on the one hand, new technologies might allow insurers to attract *new* low-risk policyholders. On the other hand, the possibility to identify different risk types and better tailor insurance contracts does not mean that high risks should be dismissed. Under some conditions, high-risk agents contribute more than low risks to the insurer's risk-bearing capacity and the mitigation of the probability of insolvency.

Our results, therefore, support the idea that the information on the individual risk level will not reduce the level of coverage offered to the high-risk agents. Moreover, we argue that this result gives an insight regarding the potential use of the available information to provide incentives for prevention and self-protection and incentivize the agents that are revealed to be high risks to lower their exposure.

Our second theoretical study (Chapter 3) analyzes an adjacent idea in a different context. We want to examine the idea that the possibility of enhanced risk classification will provide undeniable advantages to the private insurers who would use more price discrimination to attract the low-risk policyholders, and to the low-risk policyholders themselves because they would benefit from lower prices. Specifically, we are interested in the role of mutual insurers in such a context. If the idea regarding the advantage gained by the private stock insurers is true, then the mutual insurers would not be beneficial for the low-risk agents.

The role of mutuals has been studied in the context of information asymmetry, given different propositions on how mutuals provide a possibility to screen certain risk types, limit moral hazard, or prevent cream-skimming of low-risk policyholders (B. Smith and Stutzer, 1990; B. Smith and Stutzer, 1995; Ligon and Thistle, 2005;

Ligon and Thistle, 2008; Picard, 2014). Those propositions are motivated by the observation that stock and mutual insurers have co-existed in the market and continue to co-exist nowadays. Hence, some authors have explored the possible reasons for such a co-existence or have provided a comparison between the two types of insurance providers (Mayers and C. Smith, 1988; Braun et al., 2015; Bourlès, 2009; Fagart et al., 2002; Charpentier and Le Maux, 2014).

Given the co-existence between the two types of insurance providers, and the possible advantages obtained by the private insurers choosing to enhance the risk classification, we aim at exploring the conditions under which the mutual insurer would attract both the high-risk and the low-risk agents, despite the assumed absence of price differentiation.

We build a model with two types of insurers, one mutual and one stock insurer, and we focus on the differences, such as different pricing strategies and different ways of dealing with insolvency issues, which reflect the principle of solidarity of mutual insurance. Hence, we assume that the stock insurer sets individualized premiums and adds a risk loading to manage the probability of insolvency, as explained in Chapter 2. The mutual insurer does not apply any price discrimination and offers an average price, while also keeping an option of issuing an additional call on premiums if the amount of premiums collected at the beginning is not sufficient to cover the aggregate claims.

We find that it is not necessarily optimal for the low-risk policyholders to choose the stock insurance contract rather than the mutual one, even when the individualized premium is offered by a stock insurer, contrary to the idea of the advantage provided by individualization. We show that it can be optimal for the low-risk agents to participate in the mixed mutual pool with the high-risk agents by covering their risk together through the mutual insurer, depending on the weight of the low-risk group in the population and the size of the risk loading.

For instance, if the entire population is initially insured by the stock insurer, but individualized premiums make it more advantageous for the high-risk agents to choose the mutual insurer, the stock insurance portfolio will decrease in size. Given that the stock insurers must maintain a fixed level of the probability of insolvency for regulatory reasons, a decrease in the size of the portfolio will affect the premium level to compensate for the lack of reserves. Consequently, an increase in the premium level created by the high-risk agents switching from the stock insurer to the mutual insurer can provide incentives for the low-risk agents to join the mutual pool as well.

Finally, in our experimental study (Chapter 4) we design a laboratory experiment in which we compare two insurance contracts, a bonus-malus contract and a behavioral contract in the context of an individual choice game regarding the effort of prevention. We additionally examine the choice of contract type in the middle of our experiment to analyze possible determinants of individual preferences towards one or the other contract types. Our experiment is based on our theoretical predictions regarding the optimal level of prevention, provided in the first part of the chapter. Thus, we aim at exploring simultaneously the potential of behavioral contracts in providing more incentives for prevention compared to the bonus-malus contract, and the type of policyholders that would be interested in choosing such a contract.

Our main contributions consist first in the consideration of a new type of behavioral contract that exists only partially at the moment, and second in the comparison of such a contract with the more common experience-based contract. Indeed, currently, the European legislation only allows using rewards and discounts based on individual behavior. Nevertheless, given the fast development of new technologies and new products, one can easily imagine an insurance contract entirely based on the policyholders' preventive behavior rather than claims history, or at least allowing for both a positive and a negative premium adjustment rather than discounts and rewards alone. At the same time, no experimental study has been conducted on the incentives for prevention of the experience-based contracts, despite the fact that automobile insurance is often built around such experience-based systems and that one of the objectives of such systems is to promote preventive activity.

While there exists empirical literature that uses real insurance data and aims to disentangle the potential effect of preventive incentives from various sources of information asymmetry, such as adverse selection and learning (Abbring, Chiappori, and Pinquet, 2003; Abbring, Chiappori, and Zavadil, 2008; Dionne, Michaud, et al., 2013), we use the experimental setting to explicitly identify the individual investment in prevention effort and to control for relevant individual characteristics that can influence the provision of prevention effort, such as risk aversion or prudence.

We, therefore, address two original issues in our experimental analysis. First, we examine how the contract type affects the policyholders' preventive actions, namely the effort provided to reduce the probability of an accident. Second, we study the contract choice and its potential determinants. We develop a theoretical model of optimal prevention effort under two contracts, a bonus-malus contract and a behavioral contract. Then, we derive our theoretical predictions and testable hypotheses that are further used to design the experimental procedure.

Our main experiment consists of individual choice tasks regarding the prevention effort, given a bonus-malus contract. In the middle of the main experiment, subjects can switch to the behavioral contract or stay with a bonus-malus contract. Thus, we can explore both the prevention effort under two contract types and the choice of contract. We use an adapted multiple-price list (Drichoutis and Lusk, 2016) to elicit risk aversion in the gain and loss domain. In addition, we elicit the subjects' absolute risk aversion by comparing their switching point in two identical multiple-price lists with a different initial endowment. We also elicit prudence in the loss domain (Noussair et al., 2014; Brunette and Jacob, 2019), given that prudence is known to be an important determinant of prevention effort.

We find that the subjects choosing a behavioral contract provide higher levels of prevention effort than the subjects choosing a bonus-malus contract. We also observe self-selection according to the individual preferences for prevention. Precisely, the subjects providing a higher level of effort in the first part of the experiment choose to continue with a behavioral contract. We also find that the prevention effort depends on risk aversion and prudence. In particular, we find that risk-seeking individuals provide less effort to decrease their loss probability, and the same holds for the more prudent individuals.

Introduction générale

Cette thèse vise à améliorer la compréhension de l'impact des données nouvelles et massives sur le secteur de l'assurance, tout en examinant les changements potentiels apportés par le développement actuel des technologies numériques, et en particulier par les informations qui deviennent disponibles à la suite de cette transformation.

La thèse se concentre en particulier sur les changements relatifs à la segmentation et à la prévention des risques, créés par la disponibilité des informations et par les nouvelles sources de données, qui n'étaient pas disponibles auparavant. L'impact sur la couverture des hauts et des bas risques serait-il nécessairement différent ? Quelles sont les conséquences possibles pour la coexistence et les avantages comparatifs de l'assurance mutuelle et de l'assurance par actions, compte tenu de la possibilité technique d'une segmentation des risques plus fine ? La prévention, pourrait-elle être améliorée grâce aux nouveaux types de contrats ? Quels types d'assurés pourraient être intéressés par ces nouveaux contrats ? Telles sont les questions auxquelles nous tentons de répondre à travers les chapitres de la présente thèse, tout en faisant appel à différentes approches et perspectives que nous présenterons plus loin dans cette introduction.

Les questions qui constituent notre principal centre d'intérêt dans ce travail sont mises en lumière par l'état actuel du développement technologique et d'environnement numérique moderne dans lequel nous vivons. Depuis le développement rapide des *Technologies de l'information et de la communication* (TIC) et la baisse du coût des appareils connectés au cours des dernières années, l'accès à ces appareils et leur utilisation se sont généralisés. En ce qui concerne la connexion à l'internet, la part des ménages de l'UE-27 disposant d'un accès à l'internet est passée à 90% en 2019, soit 26 points de pourcentage de plus qu'en 2009 (European Commission, 2020b). En outre, l'une des six priorités de la Commission européenne pour la période 2019-2024 est *une Europe adaptée à l'ère numérique* (European Commission, 2019).

Grâce au développement des TIC, les données produites par divers appareils électroniques peuvent être collectées en continu grâce à des smartphones, des capteurs ou des boîtiers connectés, mais aussi transmises et traitées plus rapidement et à moindre coût grâce à l'augmentation des capacités de calcul. Par exemple, en une journée cinq milliards de recherches sur internet sont effectuées et quatre téraoctets[4] de données sont créées par chaque voiture connectée.[5] La Commission européenne indique que le traitement et l'analyse des données ont lieu à 80% dans les centres de données et les installations informatiques centralisées, et à 20% dans les objets connectés, tels que les voitures, les appareils ménagers ou les robots de fabrication, et ces proportions devraient s'inverser d'ici 2025 (European Commission, 2020a).

La quantité de données disponibles augmente avec le nombre d'objets connectés et le nombre de connexions effectuées. En outre, on observe un changement qualitatif concernant les données disponibles. De nouveaux types de données sont devenus accessibles, provenant de nouvelles sources telles que les données en ligne, issues des moteurs de recherche et des médias sociaux, ou les données des appareils connectés, comme les smartphones, les montres connectées et toute autre sorte de capteurs. Le nombre de voitures connectées qui peuvent envoyer et recevoir des informations grâce à la télématique est estimé à plus d'un milliard dans le monde.[6] Ainsi, les données standard sont plus faciles à collecter, par exemple grâce aux enquêtes en ligne, et sont moins coûteuses à stocker et à analyser, tandis que de nouveaux types de données deviennent accessibles, comme les données sur le comportement individuel.

Les nouvelles technologies, et plus particulièrement les TIC, ont un impact important sur toutes les industries. Mais les secteurs les plus touchés par les changements sont ceux qui reposent principalement sur l'utilisation des données, car les nouvelles technologies apportent la transformation la plus profonde en matière de la collecte et de l'analyse des données. Le secteur de l'assurance est un très bon exemple d'un marché construit autour de l'information et qui subit actuellement une transformation importante.

Les assureurs se sont toujours appuyés sur des données pour évaluer les risques individuels. Les bases de données traditionnelles utilisées pour l'évaluation des risques sont principalement construites à l'aide d'informations déclaratives directes fournies par les assurés. De nos jours, ces bases de données sont plus faciles à créer et moins coûteuses à traiter. En outre, depuis que de nouveaux types de données sont devenus disponibles, les assureurs les utilisent de plus en plus pour compléter les bases de données traditionnelles (EIOPA, 2019).

[4] Un téraoctet est égal à 1000^4 octets.
[5] "*How much data is generated each day?*", World Economic Forum, 2019.
[6] "*Connected cars worldwide*", Statista, 2020.

La dépendance entre le fonctionnement de l'assurance et l'information disponible a une conséquence principale qui constitue un sujet d'étude important en théorie économique : les questions d'asymétrie d'information. La répartition de l'information pertinente entre les deux parties du contrat, l'assureur et l'assuré, détermine de multiples façons la forme des contrats d'assurance, leur prix et la structure du marché de l'assurance.

Il est commun de partir du principe que la distribution de l'information pertinente, notamment en ce qui concerne les types de risques et les actions des assurés, n'est pas symétrique. Les assurés sont supposés avoir une connaissance complète de leurs caractéristiques personnelles en ce qui concerne le niveau de risque, et des actions qu'ils entreprennent, ou non, en relation avec l'exposition au risque. Ces éléments sont simultanément supposés être cachés à l'assureur, ce qui produit des inefficiences du marché connues sous le nom de sélection adverse et d'aléa moral. Les découvertes importantes des théoriciens de l'économie décrivent les situations dans lesquelles ces questions se posent et offrent des moyens possibles de corriger les inefficiences résultant d'une telle distribution de l'information (Akerlof, 1970; Rothschild and Stiglitz, 1978; Hölmstrom, 1979).

L'asymétrie d'information reste depuis longtemps une hypothèse pertinente, et les recherches récentes continuent de fournir des extensions importantes aux questions connexes (Picard, 2014; Mimra and Wambach, 2017; Picard, 2019). Néanmoins, face à une disponibilité croissante de l'information, il est également important de s'interroger sur la possibilité d'approcher la *symétrie* d'information. Par exemple, les discussions sur la personnalisation des contrats d'assurance, la segmentation accrue des risques et les contrats basés sur le comportement montrent que les assureurs en apprennent davantage sur les besoins, les caractéristiques et le comportement des assurés, et cette dynamique de changement de la relation entre assureurs et assurés soulève une série de nouvelles questions.

Dans ce contexte, cette thèse vise à contribuer à une meilleure compréhension de la manière dont les nouvelles données pourraient affecter le fonctionnement de l'assurance, de différents points de vue. Nous identifions une série de questions liées à l'impact de la disponibilité de l'information sur différents types de risques et différentes formes d'assurance, et à l'impact sur la prévention. L'objectif de cette thèse est de donner des éléments de réponse à ces questions, afin de contribuer au développement de meilleurs produits et services, et favoriser la réflexion sur les outils et politiques pertinents nécessaires pour accompagner la transformation numérique en cours dans le secteur de l'assurance.

Cette thèse aborde l'objectif annoncé d'un point de vue théorique et expérimental, en commençant tout d'abord par une présentation approfondie du contexte faite dans le Chapitre 1.

Dans ce premier chapitre, nous visons à dresser un tableau global et à discuter de la manière dont les aspects fondamentaux de l'activité d'assurance sont modifiés par l'accès aux nouvelles données. Une première discussion sur la situation est utile pour comprendre la nature des questions de recherche abordées dans la suite de la thèse, ainsi que les problèmes et débats découlant du contexte donné. Nous fournissons des exemples concrets de nouveaux acteurs et de nouveaux contrats et discutons des changements globaux sur le marché de l'assurance. Cela nous donne l'occasion de décrire le cadre d'étude de cette thèse, qui peut être résumée par deux questions principales liées à la segmentation des risques et à la prévention des risques.

Les questions liées à la segmentation des risques et à son impact sur les différentes parties du contrat d'assurance sont abordées dans les Chapitres 2 et 3 à travers deux modèles théoriques. Ces questions sont motivées par les conséquences potentielles que la disponibilité des informations peut avoir sur la segmentation des risques et la personnalisation des offres d'assurance, qui sont attendues des assureurs ayant un accès croissant aux informations sur les risques individuels.

Dans le Chapitre 2, nous montrons qu'un assureur privé ne s'efforcerait pas de ne garder que les assurés à bas risque, même si l'information est symétrique et que l'assureur peut parfaitement distinguer les différents types de risques. Nous fournissons une démonstration théorique de l'importance des assurés à haut risque et soulignons le fait qu'il est aussi important d'attirer de nouveaux agents à bas risque en utilisant les données disponibles sur les types de risque que de conserver les hauts risques existants. Nous développons donc un argument en faveur de l'idée que les nouvelles données devraient être utilisées pour aider ces derniers à diminuer leur exposition au risque, lorsque cela est possible.

Dans le Chapitre 3, notre analyse théorique est motivée par le point de vue lié à la question que nous abordons dans le Chapitre 2, l'idée étant que la disponibilité de l'information n'est bénéfique que pour les assureurs privés par actions et les agents à bas risque, puisque les premiers proposeront des primes moins élevées aux seconds. En particulier, nous explorons le cas de l'assurance mutuelle dans notre étude théorique et modélisons explicitement le fait que les mutuelles sont a priori moins incitées à utiliser toute l'information disponible pour segmenter les différents types de risques, par rapport aux assureurs privés par actions. Nous introduisons également différents mécanismes de gestion de l'insolvabilité, qui constituent le deuxième aspect important qui distingue l'assurance mutuelle de l'assurance par actions.

Nous examinons spécifiquement les conditions qui rendent l'assurance mutuelle plus avantageuse pour les agents à haut et à bas risque, par rapport à l'assureur privé qui appliquerait une plus grande discrimination des prix. Nos résultats peuvent contribuer à la compréhension de la coexistence entre l'assurance mutuelle et l'assurance par actions, et en outre, à souligner que la personnalisation n'est pas nécessairement souhaitable pour les assureurs par actions, et que l'assurance mutuelle peut être bénéfique dans le contexte actuel.

Dans le Chapitre 4, nous utilisons une approche théorique et expérimentale pour étudier le nouveau type de contrat d'assurance basé sur l'effort de prévention, qui n'existe pas encore sous cette forme exacte. Ces contrats comportementaux pourraient, en théorie, contribuer à promouvoir la prévention, et des offres partielles de tels contrats sont déjà utilisées par les assureurs. Nous comparons ce contrat comportemental au système classique basé sur la sinistralité, tel que le système bonus-malus, et examinons les incitations fournies par chacun, ainsi que les préférences individuelles vers l'un ou l'autre des types de contrat. Nous constatons que les sujets assurés par le biais des contrats comportementaux investissent davantage dans l'effort de prévention, et que les préférences initiales pour la prévention semblent être un déterminant important du choix du contrat lorsque les deux types de contrats sont proposés.

Nous allons maintenant présenter plus spécifiquement chacune des questions et approches de recherche qui constituent ce travail.

Cette thèse commence par l'analyse contextuelle des changements qui façonnent actuellement le secteur de l'assurance (Chapitre 1). Nous présentons un aperçu détaillé des changements que subit actuellement la pratique de l'assurance, en nous concentrant sur ceux qui sont pertinents pour les principaux sujets d'étude qui nous intéressent, à savoir la personnalisation et la segmentation des risques et l'utilisation des données comportementales pour la prévention des risques.

Notre principale contribution est de fournir un tableau global du contexte dans lequel ces transformations prennent naissance, en particulier celles qui appellent une révision de certaines hypothèses de la théorie économique et l'étude de nouvelles éventualités. Ainsi, nous visons à proposer une appréciation des nouvelles tendances et des nouveaux défis créés par le contexte actuel de l'accessibilité des données pour le secteur de l'assurance.

Pour analyser les transformations actuelles dans le secteur, nous présentons d'abord une vue d'ensemble des aspects particuliers des nouvelles données qui deviennent disponibles pour les assureurs. Nous présentons leurs caractéristiques, telles que la granularité et la nature désorganisée, et nous poursuivons en discutant des nouvelles sources d'information qui sont générées par les nouvelles technologies. Nous discutons également des nouveaux outils disponibles pour l'analyse de données plus volumineuses et désorganisées.

Ensuite, nous procédons à l'analyse des nouvelles possibilités offertes aux assureurs, en les illustrant par des exemples concrets de nouveaux acteurs émergeant sur le marché et de nouveaux produits offerts. Nous fournissons des exemples d'entreprises qui intègrent les nouvelles données et les nouvelles technologies dans leurs activités, en mettant l'accent sur deux grands secteurs d'assurance, la santé et l'automobile, étant donné qu'il s'agit des branches les plus importantes en dehors de l'assurance-vie.

Enfin, nous fournissons une analyse des deux principales questions d'intérêt dans cette thèse, à savoir la segmentation des risques et la prévention des risques. Nous examinons la manière dont ces deux éléments, historiquement importants pour le fonctionnement de l'assurance, évoluent dans le contexte actuel de la profusion des données. En particulier, nous examinons la façon dont ces éléments sont liés aux problèmes d'asymétrie d'information qui sont aujourd'hui remis en question étant donné la disponibilité des données. Nous présentons également une discussion sur diverses questions pratiques et sociétales qui émergent de ces problèmes et qui peuvent sembler théoriques au premier abord, et nous fournissons une perspective plus large pour les questions que nous abordons dans les chapitres suivants.

Notre première étude théorique (Chapitre 2) analyse l'hypothèse de la symétrie d'information et la segmentation des risques plus fine qui y est liée, en relation avec les agents à haut risque en particulier. Notre objectif est de répondre à une inquiétude et à la question soulevée par les récentes innovations dans le secteur de l'assurance concernant les agents qui se révèlent être à haut risque. Puisque l'assureur pourrait, en théorie, en apprendre davantage sur le niveau de risque individuel d'un assuré et affiner la segmentation des risques en différenciant plus les types de risques, nous nous demandons si la stratégie consistant à se concentrer uniquement sur les agents à bas risque est opportune pour les assureurs. Nous souhaitons ainsi contribuer au débat en cours sur l'impact que la disponibilité des données peut avoir sur les agents à haut risque.

Pour examiner cette question, nous présentons un modèle à une période du risque global de l'assureur, étant donné un portefeuille des risques indépendants. Nous nous concentrons donc sur le portefeuille d'assureur privé du point de vue de l'insolvabilité, et en particulier sur le rôle des assurés à haut risque. Alors que la littérature considère principalement des portefeuilles homogènes (Cummins, 1991;

M. Smith and Kane, 1994; Gatzert and Schmeiser, 2012; Albrecht and Huggenberger, 2017), nous contribuons à la discussion en considérant l'hétérogénéité et l'interaction entre cette dernière, les contraintes de solvabilité et la taille finie du portefeuille.

La raison pour laquelle nous considérons ce cadre, et en particulier les problèmes de solvabilité et la taille finie du portefeuille, est la suivante. D'une part, les assureurs européens doivent contrôler leur probabilité d'insolvabilité conformément aux conditions légales de protection des assurés (Solvabilité II). En particulier, les assureurs doivent fournir une évaluation correcte de leur risque et détenir des montants appropriés de capital qui doivent être utilisés pour maintenir la probabilité d'insolvabilité à un niveau exigé de 0,5% par an. D'autre part, nous trouvons important de considérer la taille finie du portefeuille, car elle est pertinente pour les compagnies opérant dans des branches spécifiques où le nombre d'assurés est limité, et surtout pour les nouvelles compagnies d'assurance qui entrent sur le marché.

Nous introduisons également dans notre modèle deux types de chargement de la prime, un chargement additif et un chargement multiplicatif, les deux étant les chargements de sécurité. En effet, un aspect important de la gestion de la probabilité d'insolvabilité est un fonds de sécurité qui peut être partiellement constitué des contributions individuelles à travers le chargement de la prime (Cummins, 1974; Cummins, 1991; M. Smith and Kane, 1994). Ainsi, la présence d'un chargement de sécurité permet de renforcer la capacité de couverture des risques afin de maintenir la probabilité d'insolvabilité en dessous du niveau exigé.

Nous analysons le lien entre la taille du portefeuille de l'assureur, sa composition représentée par la combinaison de types de risques hétérogènes, et leur contribution au fond de sécurité à travers les primes chargées, qui sont les éléments qui définissent le risque et la solvabilité de l'assureur. Nous obtenons nos résultats d'abord pour une distribution binaire des risques, puis pour des risques distribués normalement et nous montrons que les agents à haut risque contribuent proportionnellement plus au fond de sécurité lorsque le chargement est multiplicatif. Par conséquent, le pool peut être plus petit s'il est hétérogène ou ne contient que des hauts risques, par rapport au pool homogène de bas risques.

Lorsque les risques sont distribués normalement, les assurés à haut risque ne permettent pas nécessairement une diminution plus rapide de la probabilité d' insolvabilité, car le montant de la perte peut prendre un nombre infini de valeurs. Cependant, nous soulignons que pour un niveau fixe de probabilité d'insolvabilité, la prime est toujours décroissante avec la taille du pool, si la proportion d'agents à haut et bas risque n'est pas affectée. De plus, la prime diminue avec le niveau de risque des agents à haut risque.

Par conséquent, nous montrons qu'il n'est pas nécessairement souhaitable pour l'assureur de former un pool homogène d'agents à bas risque, du moins du point de vue réglementaire. Des pools homogènes suffisamment grands pourraient être difficiles à créer, en particulier au regard des contraintes de solvabilité imposées par les régulateurs. Ainsi, d'une part, les nouvelles technologies pourraient effectivement permettre aux assureurs d'attirer de *nouveaux* assurés à bas risque. D'autre part, la possibilité d'identifier différents types de risques et de mieux adapter les contrats d'assurance ne signifie pas que les hauts risques doivent être écartés. Sous certaines conditions, les agents à haut risque contribuent davantage que les agents à bas risque à la capacité de l'assureur à couvrir les risques et à la gestion de la probabilité d'insolvabilité.

Nos résultats soutiennent donc l'idée que l'information sur le niveau de risque individuel ne réduira pas le niveau de couverture offert aux agents à haut risque. De plus, ce résultat donne une idée quant à l'utilisation potentielle de l'information disponible pour fournir des incitations à la prévention et à l'auto-protection et accompagner les agents qui se révèlent être à haut risque vers la réduction de leur exposition.

Notre deuxième étude théorique (Chapitre 3) analyse une idée connexe dans un contexte différent. Nous examinons l'idée selon laquelle la possibilité d'une segmentation des risques plus fine offrira des avantages indéniables aux assureurs privés qui utiliseront la discrimination par les prix pour attirer les assurés à bas risque, et aux assurés à bas risque eux-mêmes, car ils bénéficieront de prix plus bas. Plus précisément, nous nous intéressons au rôle des mutuelles dans un tel contexte. Si l'idée concernant l'avantage obtenu par les assureurs privés par actions est vraie, alors les mutuelles ne seront pas bénéfiques pour les agents à bas risque.

Le rôle des mutuelles a été étudié dans le contexte de l'asymétrie d'information, avec différentes propositions sur la manière dont les mutuelles permettent de séparer différents types de risques, de limiter l'aléa moral ou d'empêcher l'écrémage des assurés à bas risque (B. Smith and Stutzer, 1990; B. Smith and Stutzer, 1995; Ligon and Thistle, 2005; Ligon and Thistle, 2008; Picard, 2014). Ces propositions sont motivées par le fait que les assureurs par actions et les mutuelles ont longuement coexisté sur le marché et continuent de coexister de nos jours. Ainsi, certains auteurs ont exploré les raisons possibles d'une telle coexistence, en proposant une comparaison entre les deux types de fournisseurs d'assurance (Mayers and C. Smith, 1988; Braun et al., 2015; Bourlès, 2009; Fagart et al., 2002; Charpentier and Le Maux, 2014).

Étant donné la coexistence entre ces deux types d'assureurs et les avantages possibles obtenus par les assureurs privés qui choisissent de segmenter plus finement, nous cherchons à explorer les conditions sous lesquelles l'assureur mutualiste attirerait à la fois les agents à haut et à bas risque, malgré l'absence supposée de différenciation des prix.

Nous construisons un modèle avec deux types d'assureurs, un assureur mutualiste et un assureur par actions, et nous nous concentrons sur les différences entre les deux, telles que les différentes stratégies de tarification et les différentes manières de traiter les problèmes d'insolvabilité, qui reflètent le principe de solidarité de l'assurance mutuelle. Nous supposons donc que l'assureur par actions fixe des primes individualisées et ajoute un chargement de sécurité pour gérer la probabilité d'insolvabilité, comme expliqué au Chapitre 2. L'assureur mutualiste n'applique aucune discrimination de prix et offre un prix moyen, tout en gardant la possibilité de faire un recours au rappel de cotisations si le montant des primes collectées au début n'est pas suffisant pour couvrir les sinistres globaux.

Nous montrons qu'il n'est pas nécessairement optimal pour les assurés à bas risque de choisir le contrat d'assurance par actions plutôt que le contrat mutuel, même lorsque l'assureur privé propose les primes individualisées, contrairement à l'idée de l'avantage fourni par une telle possibilité. Nous montrons qu'il peut être optimal pour les agents à bas risque de faire partie d'une mutuelle avec les agents à haut risque, en couvrant leur risque ensemble à travers l'assureur mutualiste, en fonction du poids du groupe à bas risque dans la population et de la taille du chargement de la prime.

Par exemple, si l'ensemble de la population est initialement assuré par l'assureur par actions, mais que les primes individualisées font de sorte à ce qu'il soit plus avantageux pour les agents à haut risque de choisir l'assureur mutualiste, le portefeuille d'assurance par actions diminuera en taille. Étant donné que les assureurs par actions doivent maintenir un niveau fixe de probabilité d'insolvabilité pour des raisons réglementaires, une diminution de la taille du portefeuille affectera le niveau des primes afin de compenser le manque de réserves. Par conséquent, une augmentation du niveau de prime créée par les agents à haut risque quittant l'assureur par actions pour choisir la mutuelle peut inciter les agents à bas risque à rejoindre également la mutuelle.

Enfin, dans notre étude expérimentale (Chapitre 4), nous mettons en place une expérience de laboratoire dans laquelle nous comparons deux contrats d'assurance, un contrat bonus-malus et un contrat comportemental, dans le contexte d'un jeu de choix individuel concernant l'effort de prévention. Nous examinons en outre le choix du type de contrat au milieu de notre expérience afin d'analyser les déterminants possibles des préférences individuelles pour l'un ou l'autre type de contrat. Notre expérience est basée sur nos prédictions théoriques concernant le niveau optimal de prévention, fournies dans la première partie du chapitre. Ainsi, nous visons à explorer simultanément le potentiel des contrats comportementaux à fournir plus d'incitations à la prévention par rapport au contrat bonus-malus, et le type d'assurés qui seraient intéressés à choisir un tel contrat.

Nos principales contributions consistent d'abord en la considération d'un nouveau type de contrat comportemental qui n'existe que partiellement à l'heure actuelle, et ensuite en la comparaison d'un tel contrat avec le contrat plus commun basé sur l'historique de sinistralité. En effet, actuellement, la législation européenne ne permet que l'utilisation de récompenses et de rabais basées sur le comportement individuel. Néanmoins, étant donné le développement rapide des nouvelles technologies et des nouveaux produits, on peut facilement imaginer un contrat d'assurance entièrement basé sur le comportement préventif des assurés plutôt que sur l'historique des sinistres, ou du moins permettant un ajustement positif et négatif de la prime. En même temps, aucune étude expérimentale n'a été menée sur les incitations à la prévention des contrats basés sur l'historique de sinistralité, malgré le fait que l'assurance automobile est souvent construite autour de tels systèmes basés sur l'expérience et que l'un des objectifs de ces systèmes est de promouvoir l'activité préventive.

Alors qu'il existe une littérature empirique qui utilise des données d'assurance réelles et vise à séparer l'effet potentiel des incitations à la prévention de diverses sources d'asymétrie d'information, telles que la sélection adverse et l'apprentissage (Abbring, Chiappori, and Pinquet, 2003; Abbring, Chiappori, and Zavadil, 2008; Dionne, Michaud, et al., 2013), nous utilisons le cadre expérimental pour identifier explicitement l'investissement individuel dans l'effort de prévention et pour contrôler les caractéristiques individuelles pertinentes qui peuvent influencer le niveau de l'effort de prévention, telles que l'aversion au risque ou la prudence.

Nous abordons donc deux questions originales dans notre analyse expérimentale. Premièrement, nous examinons comment le type de contrat affecte les actions préventives des assurés, à savoir l'effort fourni pour réduire la probabilité d'un accident. Deuxièmement, nous étudions le choix du contrat et ses déterminants potentiels. Nous développons un modèle théorique de l'effort de prévention optimal sous deux contrats, un contrat bonus-malus et un contrat comportemental. Ensuite, nous dérivons nos prédictions théoriques et nos hypothèses testables qui sont ensuite utilisées pour élaborer la procédure expérimentale.

Notre expérience principale consiste en une tâche de choix individuel concernant l'effort de prévention, compte tenu d'un contrat bonus-malus. Au milieu de l'expérience principale, les sujets ont la possibilité de passer au contrat comportemental ou de conserver le contrat bonus-malus. Ainsi, nous sommes en mesure d'explorer à la fois l'effort de prévention sous deux types de contrat, et le choix du contrat. Nous utilisons une liste de prix multiples adaptée (Drichoutis and Lusk, 2016) pour mesurer l'aversion au risque dans le domaine des gains et des pertes. De plus, nous élicitons l'aversion au risque absolue des sujets en comparant leur point de changement dans deux listes de prix multiples identiques avec une dotation initiale différente. Nous élicitons également la prudence dans le domaine des pertes (Noussair et al., 2014; Brunette and Jacob, 2019), étant donné que la prudence est connue pour être un déterminant important de l'effort de prévention.

Nous trouvons que les sujets choisissant un contrat comportemental fournissent des niveaux d'effort de prévention plus élevés que les sujets choisissant un contrat bonus-malus. Nous observons également une auto-sélection en fonction des préférences individuelles en matière de prévention. Précisément, les sujets fournissant un niveau d'effort plus élevé dans la première partie de l'expérience choisissent de continuer avec un contrat comportemental. Nous constatons également que l'effort de prévention dépend de l'aversion au risque et de la prudence. En particulier, nous constatons que les individus averses au risque fournissent moins d'effort pour diminuer leur probabilité de perte, et il en va de même pour les individus plus prudents.

Chapter 1

The insurance sector in the new digital era

Summary of the chapter

In this chapter, we present a detailed overview of the ways in which different aspects of the insurance business are modified with access to the new data, in particular regarding the market structure and the insurance products. Our main contribution is to provide an understanding of the background from which these transformations originate, with a special focus on personalization, risk classification, and the use of behavioral data for risk prevention. We provide an analysis of new possibilities available to the insurers and illustrate them with concrete examples of new actors emerging in the market and new products being offered. Finally, we examine the issues of risk classification and risk prevention in the light of the current data availability challenging the information asymmetry hypothesis. We also provide a discussion on various practical and societal questions emerging from those issues and offer a broader perspective for the questions that we address in the following chapters.

Keywords: classification, insurance, personalization, prevention, telematics

JEL classification: D80, G22

1.1 Introduction

New technologies bring changes to all industries, but in particular to those relying on data. The insurance sector is a typical case of an industry that is based on data usage. While in other sectors new information is essentially used for marketing and sales rather than production, the information is the core of the insurance business and it affects the production itself. Hence, access to the new data has a profound impact on the insurance market.

The objective of this chapter is to dress a global picture and discuss how the fundamental aspects of the insurance business are modified with access to the new data. As we will discuss in the present chapter, two major changes can be observed in the market structure and insurance products. The market structure changes through the entry of new actors, while new contract types enrich the insurance offer.

The insurance market is a well-studied subject in economics. Still, it remains a particular object of study, since the matter exchanged in this market, the risk, is quite different from what is traded in other markets. Here, some agents that are subject to the risk of loss and desiring not to bear the monetary consequences, are looking for sharing this risk or transferring it to the external risk bearers.

The risk-sharing can be organized through risk pooling, or risk mutualization, which can take the form of mutual insurance. The risk transfer implies that an insurance company that has means of diversifying its portfolio of risks accepts to do it for payment, or insurance premium. Although insurance was existing at the beginning in some forms such as tontines and mutuals without relying on statistical risk estimation, modern insurance, be it mutual or stock, is based on the use of information in order to assess and manage the risk and set the price.

Indeed, insurance is characterized by an inverted production cycle: the price has to be determined before knowing the cost of the product, the latter being the insurance contract (Charpentier and Denuit, 2005). The inversion of the production cycle has two consequences. First, the insurance business is profoundly linked to the actuarial sciences and to the statistical tools used to evaluate the variability of potential losses and estimate the insurance premium. And second, the insurance business is dependent on the information in relation to the risk that the insurer or the insured know, and on the ways it is distributed between two sides of the contracting arrangement.

The development of the insurance business is undoubtedly due to the development of data collection, probabilities calculus, and statistics. Mortality tables and existent statistical data on the general population were used to evaluate global risk. The development of insurance is thus linked to the emergence of statistical analysis and data treatment techniques, and in particular to the actuarial science that tackles specifically the statistical analysis applied to the risk. The risk coverage and the conception of insurance products as we know them today seem unthinkable without data and statistical tools.

While information is the core of insurance business functioning, the access to the information was limited, as were the available sources of data upon a recent date. This observation, coupled with the dependence on the distribution of relevant information between contracting sides, the insurer and the insured, made insurance being one of the central subjects of study related to the information asymmetry issues.

Insurance coverage represents a contract, and the object of this contract, the risk, is, in general, at least partially endogenous. Hence, on the one hand, it is assumed that the characteristics which are important for the evaluation of the agent's "type" or, in the context of insurance, the policyholder's risk level, are unknown for the insurer. On the other hand, the agent's behavior that determines the risk level is complicated to be observed. Thus, policyholders are traditionally considered to be better informed about their risk and the actions undertaken to manage the individual exposure to it.

Those two hypotheses form the basis of what is known in economic theory as adverse selection and moral hazard. Seminal research papers are dedicated to the propositions on how to deal with those issues and with inefficiencies that they create. The fact that the insurance market provides space for both moral hazard and adverse selection has lead to the number of important findings directly related to the subject of insurance coverage.

The adverse selection is due to the impossibility to distinguish between different risk types. It creates the situation illustrated by Akerlof's lemon market (Akerlof, 1970), where the impossibility to distinguish between the "good" products and "lemons" (products of bad quality which are impossible to identify as such) results in a market where only the lemons are traded.

Rothschild and Stiglitz (1978) show that the adverse selection issue in the insurance market can be solved by a mechanism of auto-selection based on the insurer offering a menu of contracts such as each contract is designed for a specific risk type. In this case, each contract specifies not only the price but also the amount of coverage, in the way that each combination appeals only to the risk type it was designed for. Such a menu of contracts leads each type to choose the appropriate contract without the insurer knowing ex-ante the individual risk level of each agent.

The moral hazard is related to the impossibility of neither observing nor controlling directly the agent's actions after the contract is signed. Specifically, ex-ante moral hazard consists in agents being incentivized to provide no effort to mitigate the risk when the full coverage is provided by the insurer. Ex post moral hazard is related to the incentives to fraud by falsely claiming a loss or by claiming an amount higher than the actual loss.

Living in a current digital era, we assist to the development of new technologies that facilitate the collection of information and create new sources of data, allowing us to generate qualitatively different and richer information. The data coming from new sources is more voluminous and more detailed. Besides, digital technologies provide new tools to treat and analyze this information, such as machine learning algorithms, for example. Nevertheless, the main change is the access to the new sources of data, the technologies of continuous collection of information and the computing capacity that allows treating this data.

For the insurance business, such a development means the possibility to acquire more information on the individual risk types and, potentially, to alleviate the information asymmetry issues, providing behavioral data to refine premiums, promote preventive actions, and prevent fraud. Additionally, it could stimulate the evolution of the insurer's role into the one of advisor.

The possibility of enhanced risk classification and risk prevention is the subject of the study presented in this thesis. The present chapter, in particular, aims to provide the underlying context of the transformations in the insurance sector triggered by digital technologies. The application that data accessibility and new digital tools find in the insurance business gives rise to the questions that we aim to address in the rest of this work. Hence, the main points discussed in this chapter will be further addressed in the corresponding parts, to which readers are invited to refer for additional details and review of related academic literature.

The present chapter proceeds as follows. We open with a discussion on the data that becomes available in Section 1.2, presenting the characteristics of the new data, which are different from the information previously used for risk assessment. We follow with the presentation of the new sources of information and the new tools of data analysis. In Section 1.3, we explore the applications that these technologies and information have in the insurance business. We provide examples of companies that use it and of the ways they do it, followed by the illustrations applied to the health and the automobile insurance sectors in particular. Finally, in Section 1.4, we discuss the implications of the information availability related to risk classification and risk prevention. Section 1.5 concludes with a presentation of the way in which the main questions are addressed in the following chapters.

1.2 New data and new tools originating from digital technologies

1.2.1 New kinds of available data

Insurers were historically relying on data to assess global or individual risks, such as aggregate data on the population as a whole, individual age or place of living. This type of information represents what is called traditional datasets. It has been used to create risk classes by grouping individuals with apparently similar "objective" characteristics in more or less homogeneous groups and assign the same pure premium level to the entire class.

One of the characteristics of those traditional datasets is that the information that constitutes them is declarative and provided by policyholders through surveys during the underwriting stage when the contract is signed. The International Association of Insurance Supervisors (IAIS) qualifies this type of information as direct (IAIS, 2020).[1]

Since the fast development of technologies, new types of data from new sources have become available to insurers. Hence, in some cases, it has a different quality than the traditional data. It can be indirect data, such as data from smartphones, other connected mobile devices, sensors, *Global Positioning System* (GPS) and satellite-based systems. Overall, both traditional and non-traditional datasets are increasingly available due to technological innovations, allowing easier access to data and creating new sources of information. In particular, new types of data are combined with traditional data, as stated by insurers (EIOPA, 2019). The latter does not aim to replace traditional historical and declarative data, but about using both in an attempt to gain new insights and develop new tools of data analysis.

It is more voluminous, so more generous data is available, but also more detailed and even precise. Common to all new types of data is the characteristic that is often used to describe newly accessible information: the *granularity*. Granularity being the quality of including a lot of small detail (*granularity, n.* 2013), in the context of information it refers to the level of detail at which data are stored in a database (Harrington, 2016). The new sources of information and the associated increase in details might allow insurers to improve the risk analysis and, as it is sometimes claimed, to predict consumers' behavior.

Another distinction that is commonly used when describing new data is the distinction between "hot" and "cold" data. These are technical terms related to

[1] IAIS is a nonprofit organization of insurance supervisors and regulators founded in 1994 (from over 190 jurisdictions in more than 140 countries).

data storage: cold data is rarely accessed, while hot data is accessed frequently. By extension, these terms are also used to describe data that does not change much, as historical datasets, compared to the data which is changing frequently, such as stock exchange board for example.

In fields such as marketing, cold data describes the information that stays stable over time and can be used later or permanently once collected, such as consumers' dates of birth. Hot data describes recently collected data that must be rapidly treated and analyzed to provide the best possible use for the commercial goals. For instance, data on online behavior can be used to predict an intention to buy the product or an intention to leave or break the contract. It can be used to target consumer groups or to prevent customer attrition.

It must be noted that we deliberately choose, in this thesis, not to refer to the information becoming available to the insurers as to *big data*. The reasons for this decision are the following. Our main point of interest is the fact that it becomes currently possible to use more information for risk classification and prevention. Consequently, we do not discuss the particularities of big data, such as high velocity for example (the rate of generation and analysis of big data), and we discuss only briefly the potential issues created by the techniques used to treat it, such as algorithms and machine learning.

In 2016, *Financial Conduct Authority* (FCA) has issued a statement following their call for inputs on big data in insurance.[2] This statement declares that by referring to big data, the authors refer to the practices of using new or expanded datasets, including from unconventional sources, such as social media; to the practices of adopting the technologies required to generate, collect and store these new forms of data; to the practices of using advanced data processing and analytical techniques such as predictive analytics; and to the application of resulting knowledge in business decisions and activities (FCA, 2016). In the same spirit, we want to focus in particular on the fact that more information is available today to insurers, and discuss new ways of using it. In the rest of this section, we will describe new types of data available to the insurers, new sources, as well as tools of analysis. We will follow with the examination of the impact that new data has on the sector, both from the perspective of the new nature of the information, and the applications that result from this information availability.

[2] FCA is a financial regulatory body in the United Kingdom, which serves as the conduct regulator and the prudential supervisor for financial services firms and financial markets.

1.2.2 New sources of information

The main new sources of data, as identified by FCA, are proprietary data generated internally by the firm or provided by its customers, data from third parties such as search engines data, social media data, and data from connected devices (FCA, 2016). These new types of information can be grouped into two global sources particularly relevant for the insurance sector. The first is data on online behavior, in particular from social media, online shopping, and search activity, and the second is data from various sensors (Keller et al., 2018). This second type of data is related to the connected devices installed in cars, as well as to smartphones, wearable devices, such as watches, and connected appliances, such as fire alarms and sprinklers in "smart homes".

The networks of data-generating sensors and connected devices are generally referred to as *Internet of Things* (IoT). The most known example of IoT in insurance is telematics insurance. Telematics is the area of technology that deals with sending digital information over long distances using wireless forms of communication (*telematics, n.* 2013). This term is often used to describe the connected tracking devices in vehicles, such as black boxes, and even to refer to car insurance based on data from such devices.[3]

Some other examples of devices applied to insurance are sensors in houses and farms used to alert policyholders about risks of flood, fire, bad weather conditions, or security breaches, or even prevent all of the cited. For example, British Gas, which is an energy and home services provider in the United Kingdom, offers the security cameras Hive which can be monitored through the smartphone application. Another example is Nest, which was launched in 2011 and was specializing in connected learning thermostats that optimized heating and conserved energy. The product's mechanism is based on a machine-learning algorithm that takes the sample data provided by the user adjusting the temperature during the first week as a reference, and auto-regulates afterward. The brand was acquired by Google and is now marketed under the name Google Nest, and it offers other smart devices such as cameras, doorbells, alarm systems, locks, and smoke alarms.

Other connected devices such as wearables and watches can also be linked to insurance. Those devices can collect and send information such as biometric data on the pulse, blood pressure, blood sugar level, sleep patterns, physical exercise information, and other health-related indicators which can be analyzed for insurance

[3]Description given by the British insurance company Insure The Box founded in 2010, which uses telematics devices to offer rewards and renewal premium discounts based on driving behavior: https://www.insurethebox.com/telematics.

purposes. Examples of brands offering such devices are Fitbit activity trackers and Apple watches.

As stated in the OECD report, there are few examples of home telematics being used to offer insurance discounts, despite the existence of premium discounts rewarding traditional security measures such as fire alarms (OECD, 2020). Health data and driving data are used more often, and we will provide some examples of insurance products based on the related information in the following sections.

1.2.3 New tools of data analysis

New types of data are often granular, frequently changing and heterogeneous by structure or even unstructured. Data on consumers' behavior collected online or through connected objects represents unorganized datasets, in contrast to the traditional data (OECD, 2020). Hence, new techniques of computation and data analysis are being developed to process and treat the big amounts of unstructured data which becomes available nowadays.

The branch of *Artificial Intelligence* (AI) research, such as machine learning consisting in the development of self-improving algorithms is one of the tools associated with processing and analysis of such datasets. Machine learning algorithms are used to build models for making predictions or making decisions without explicit intervention. Those techniques are sometimes referred to as big data analytics (IAIS, 2020).

We do not discuss in due detail the promising nature of those computational techniques, nor the risks associated with the use of algorithms, given that it is not the main point of interest in this thesis. Nevertheless, as we mentioned above, the development of machine learning can enable the possibility to take decisions without human intervention. While it can facilitate automation which might be efficient in some cases, it should be also taken with precaution. In particular, self-learning algorithms and the programmed decision rules are not transparent enough and might become increasingly opaque and unclear. The important societal questions such as accountability in the algorithmic decision making, readability of results, and discrimination related to the perpetuation of human biases are creating debates around the use of those tools (IAIS, 2020; Mullainathan and Obermeyer, 2017).

The amount of available data is increasing following the development of new technologies, which also produce new ways of analyzing data, giving rise to new analytical tools. Moreover, both new data and new analytical tools provide new applications for the insurance practice. In the insurance sector, access to data that is richer and potentially more precise can help insurers to develop new services, refine their risk classification and offer more individualized contracts. In the following section, we discuss the changes in the insurance sector and some examples of new companies and new services that are introduced to the market.

1.3 New data shapes the insurance practice and the insurance sector

1.3.1 New possibilities that create new companies

New applications can be sorted into three categories depending on the branches of the insurance business to which they are related: automation, distribution, and proposition (Keller et al., 2018).

First, it is possible to automate some processes related to the insurance business, such as underwriting and claims handling. American start-up Lemonade and French startup Shift Technology both use AI to offer innovative insurance products. Lemonade uses AI to simplify its policy offering procedures, tailor the contract offered to the needs of the consumer and speed up claims payments. Shift Technology uses AI to help insurers automate their claims assessment by using the automatic validation of claim details and reports by comparison with the policy terms. Moreover, Shift Technology also offers an AI-based solution to identify suspicious claims and prevent fraud.

Second, it is possible to introduce new ways of interaction with customers through mobile applications, by means of virtual assistants, or to apply targeted marketing. A French insurer GAN Prévoyance has partnered with a French startup DreamQuark that develops AI-based solutions for the financial and insurance sectors. They have developed an algorithm-based product aimed to better tailor marketing campaigns for new clients by predicting customer propensity for pensions, retirement or savings insurance products.[4] DreamQuark has also partnered with AG2R La Mondiale to create a tool aimed to decrease attrition rates. The solution uses algorithms to detect clients that might presumably decide to leave, which gives the insurer a possibility to prevent the loss of customers. A French mutual insurer MAIF had also developed a tool that uses behavioral data on web surfing to detect the policyholders that are likely to be hesitant about keeping their contract.[5]

[4] *"GAN Prévoyance selects DreamQuark for its artificial intelligence applications"*, February 1, 2018: https://www.dreamquark.com/gan-prevoyance-selects-dreamquark/.

[5] *"Relation client: entretenir le contact, une affaire de personnes?"*, L'Argus de l'Assurance, March 7, 2019: https://www.argusdelassurance.com/les-assureurs/relation-client-entretenir-le-contact-une-affaire-de-personnes.143465.

Last, technologies allow creating new products and offers, such as peer-to-peer insurance, on-demand insurance, and usage-based insurance. A German insurer Friendsurance uses its digital platform to provide peer-to-peer insurance contracts since 2010. Another German startup, One, is the first fully digital licensed European Insurance Carrier launched in 2018.[6] One uses AI and IoT devices to promote the protection and has recently introduced its application OneCoach as a joint venture with Munich Re. The application aims to help policyholders to assess their risk and provides rewards and personalized insurance packages based on their personal lifestyle. It uses the smartphone's GPS module to collect data on the user's location and movements and to offer preemptive protection guidance. It also offers real-time short-term insurance contracts that can be purchased instantly for an ongoing trip or for the duration of the journey, which can be launched automatically using the same GPS module. Additionally, the German insurer uses encryption technology to protect personal data and claims to transfer and store anonymously the information on health, movements, or location, as well as to offer full transparency on data processing to the policyholders.[7]

Another French insurance startup Luko, operating in the home and property insurance sector as well as Lemonade, has recently launched a test program for existent policyholders, aiming to introduce additional prevention services based on the IoT devices for risk prevention. The policyholders joining the program can test three connected devices to mitigate the risk of fire damage, water damage, and burglary. The French insurer also offers a premium discount to the policyholders that install a smart alarm system from a partnering company Netatmo.

Apart from life insurance, two big insurance sectors are health and automobile insurance: the former because everybody is exposed to the health risks, and the latter because vehicle insurance is often compulsory. According to the French Insurance Federation (*Fédération Française de l'Assurance*), the total amount of premiums in health insurance was 24.8 billion euros in 2019, and 22.8 billion euros in automobile insurance the same year, making these branches the second and the third biggest insurance sectors in France. We will continue to discuss the ways in which new data and technologies are integrated into insurance contracts by examining these two sectors in particular.

[6] It was acquired by Wefox, the German digital insurance platform launched in 2015.

[7] According to the Wefox Group Privacy policy: https://www.wefoxgroup.com/privacy-policy/.

1.3.2 Health insurance and personal data

Health insurance is an attractive sector for the application of new technologies. It is especially the case in the United States, where health coverage is more expensive than in Europe, and access to the medical care market is more restricted. The attractiveness is also related to the fact that the number of wearable devices, such as smartwatches or fitness trackers, is continually increasing. It is estimated to increase from 526 million devices reported in 2016 to 1.1 billion in 2022.[8]

The examples of insurers starting to use data from new sources, in particular from connected objects, are numerous. For instance, an American health insurer Aetna had a partnership arrangement with Apple since 2016 and offers to its policyholders Apple Watches for a lower price as a reward in exchange for healthy behavior. In 2019, the insurer launched a wellness program that provides incentives for a healthy activity and personalized health recommendations by using the data from the connected watches to set wellness goals.[9]

Despite the fact that Apple's partner does not offer any behavior-based direct monetary rewards in the United States, in September 2020 Apple has partnered with the government of Singapore to launch a two-year health-promoting program. Financial rewards are offered to the residents with Apple Watch who can earn one-time rewards up to 280 US dollars for healthy activities or public health actions like immunization.

In Europe, Generali France has partnered with a start-up Discovery in 2017 in order to launch a reward program Vitality for its policyholders. The rewards consist of gift cards and discounts from partnering businesses offered for healthy activities and preventive behavior, preventive efforts being the number of steps per day, medical check-ups, or type of groceries made. Discovery claims that the medical expenses of policyholders in the Vitality program are 20% lower on average than those for other insureds.

In France, the rewards do not include direct premium discounts, since the legislation is more restrictive regarding medical data than, for instance, the US legislation. In particular, the French law prohibits the price discrimination based on personal health data.[10] Vitality program is also offered by the American life insurer John Hancock and allows the policyholders enrolled in the program to save up to 15%

[8] According to Statista, a German company specializing in market and consumer data: https://www.statista.com/statistics/490231/wearable-devices-worldwide-by-region/.

[9] Aetna was bought by CVS Health, which is an American healthcare company that owns a retail pharmacy chain, and the arrangement with Apple is still maintained.

[10] Loi n° 89-1009 du 31 décembre 1989 renforçant les garanties offertes aux personnes assurées contre certains risques: https://www.legifrance.gouv.fr/loda/id/JORFTEXT000000709057/1990-01-02/.

of the annual premium. The discount and other rewards are based on the health data provided through wearable devices such as Fitbit or Apple Watch. Recently, the American insurer has also announced its partnership with Amazon and will become the first life insurer to integrate Amazon Halo, a wearable fitness device and a smartphone application for wellness and lifestyle tracking.[11]

There are other French startups in the health sector that offer innovative health insurance products. A French insurtech start-up Alan founded in 2016 is the first new independent insurance licensed in France since 1986 by the French Prudential Supervisory Authority (ACPR in French) and the first digital health insurance company in Europe. It offers a possibility to have a text discussion with a doctor, schedule a telehealth appointment, receive personalized reminders about medical consultations or vaccination, and store health-related documents.

Due to the nature of data involved, health insurance and medical data are obviously subject to close examination by both regulators and the public. The business deal that has recently created a debate and a negative public response is the acquisition of fitness monitor tracker company Fitbit by Google. The announcement has created both competition and privacy concerns and has generated a negative response from consumer protection and human rights groups regarding the use of personal data for commercial advertising.[12]

European Commission has extended the decision deadline on the aforementioned acquisition from October 2020 until January 2021. In the article issued by Vox EU, the economists express their concern about the potential dominance of one company in the space of health-related data and about the possible connection between privacy issues and market power.[13] The authors highlight the fact that such an acquisition would allow Google to combine health data with other data owned by the company and lead to the personalization of offers in health insurance. Thus, the authors express concern about "health tech" in general and the fact that personalized offers do not mean primarily lower prices to good candidates, but higher prices and critically lower cover to others.

[11] *"Amazon and John Hancock Announce Strategic Collaboration Aimed at Helping Customers Improve Their Health and Wellness"*, August 27, 2020: https://www.johnhancock.com/about-us/news/john-hancock/2020/08/amazon-and-john-hancock-announce-strategic-collaboration-aimed-at-helping-customers-improve-their-health-and-wellness.html.

[12] It has also produced concerns regarding the monopoly issues. The U.S. Justice Department accused Google of illegally protecting its monopoly over search and search advertising. The lawmakers also accused Apple, Amazon, and Facebook of abusing their market power and called for the enforcement of antitrust laws: https://www.nytimes.com/2020/10/20/technology/google-antitrust.html.

[13] Vox EU is an online policy portal launched by the Centre for Economic Policy Research (CEPR) to promote research-based policy analysis: https://voxeu.org/article/googlefitbit-will-monetise-health-data-and-harm-consumers.

1.3.3 Automobile insurance and telematics

The biggest sector where new technologies and new data have created new insurance products is the automobile insurance sector. The insurance contracts that are tailored based on the usage or the behavior are referred to as *Usage-Based Insurance* (UBI). This umbrella term applied to car insurance includes the insurance coverage based on the actual usage, such as the insurance coverage based on kilometers driven (*Pay-As-You-Drive* (PAYD)), or the insurance coverage based on the driving behavior estimated from the data collected through the black boxes (*Pay-How-You-Drive* (PHYD)).

In the case of PHYD insurance, telematics data, which is collected and transmitted via GPS, include information such as driving speed, harsh braking, acceleration, cornering, or time of the day the journey is made. The insurers often collaborate with third-party services that provide them with the results of data analysis. In particular, those firms calculate "scores" based on the indicators of driving behavior collected through telematics. Those scores are then used by insurers to offer discounts to the policyholders showing good driving behavior.

The UBI contracts have been introduced to the market for some time.[14] Nevertheless, the rate of personal telematics insurance policies is growing, and new strategic uses of telematics data continue to develop. For instance, an American insurer Metromile offering a distance-based PAYD insurance has recently made a strategic move by starting to offer a free insurance quote based on the telematics data since October 2020.[15] Users can download a smartphone application that tracks their mileage and other driving data during two following weeks. Then it calculates a free estimation for their potential insurance premium and the coverage suitable for their needs. This offer is designed to help potential customers to better understand the benefits of UBI and attract new clients interested in such individualized insurance contracts, given that such an option is not commonly available to try for free. Other big American auto insurers offering UBI programs, such as Progressive and Allstate, provide usage-based premiums only to the actual policyholders on the first purchase of coverage. Another example of strategic innovation in telematics insurance is given by the UK insurer Cuvva, which offers PAYD insurance coverage since 2016. Cuvva has recently launched a new flexible pay-monthly motor insurance coverage which can be canceled at any time.[16]

[14] An American insurer Progressive has launched a PAYD program called MyRate in 2008.

[15] "Insurtech Metromile is offering free quotes for usage-based policy", *The Business Insider*, October 15, 2020: https://www.businessinsider.com/metromile-us-pay-per-mile-insurtech-launches-new-app-feature-2020-10.

[16] https://www.cuvva.com/car-insurance/temporary.

The largest markets for telematics insurance are the US, Canada, Italy, and the UK. In North America, the telematics market is represented by such big insurance companies as Progressive, Allstate, Liberty Mutual, Nationwide, and State Farm in the US, as well as Intact Financial Corporation and Desjardins in Canada. In Europe, more than 50% of telematics insurance contracts are offered by the Italian insurers UnipolSai and Generali.[17] Italy represents one of the biggest European markets for telematics insurance because the Italian legislation recommends the installation of telematics devices to all car insurance providers and the use of telematics data to set premiums since 2017. The Italian Insurance Association estimates that telematics boxes have been installed in over 2 million of cars in Italy (OECD, 2017).

The UK software company The Floow provides automobile insurers, car-makers, and fleet operators with telematics solutions. The company has recently launched a smartphone-based crash detection service.[18] It is based on a machine-learning algorithm that uses data from crash tests to analyze it and compare it to the real-life claims database from multiple insurance providers. The algorithm is then used to assess the factors and conditions of each journey in real-time and evaluate if a high severity incident has taken place. It is also able to issue a crash report based on crash data, allowing for quick intervention by roadside assistance and quick claim handling. The company has also developed the first UK telematics insurance coverage based only on a smartphone application, in collaboration with Direct Line Group, one of the main UK insurers offering UBI contracts.

Based on the survey conducted on the pool of European car owners by Israeli startup Otonomo, more experienced consumers express more interest in UBI contracts.[19] The consumers most interested in UBI contracts are Italian and British drivers. In terms of age group, younger drivers appear to be more interested, which is not surprising given that younger policyholders generally pay higher insurance premiums. An interesting discovery is that a significant proportion of respondents declared not to be interested in discounted insurance based on driving data, especially in France and Germany (21 and 18% respectively, compared to 12 and 13%

[17] According to Business Wire, on the basis of the report made by Research and Markets, "Insurance Telematics in Europe and North America, 4th Edition", 2019. The report also states that other industries are increasingly involved in telematics insurance, in particular automobile manufacturers such as General Motors, Honda, BMW, Daimler, Hyundai and Toyota.

[18] https://www.thefloow.com/latest/introducing-our-smartphone-based-crash-detection-service/.

[19] Otonomo provides a cloud-based software platform that captures and anonymizes vehicle data which can be further used to create services such as subscription-based fueling, usage-based insurance and emergency service: https://techcrunch.com/2020/05/01/otonomo-raises-46-million-to-expand-its-automotive-data-marketplace/.

in Italy and UK). The same trend can be observed in those countries regarding the willingness to share data to get discounted insurance.[20] The social acceptability of UBI contracts is naturally linked to the cultural aspects, which are also reflected in the legal requirements known to be more strict in Europe, and in particular in France and Germany, compared to the United States, for example.

The insurance companies seem to be taking seriously the ongoing digital transformation. Generali, the third largest insurance company in the world, plans to add changes since it has been affected by the ongoing coronavirus pandemics through the shutting down of its main distribution channels (insurance sales agencies).[21] The plan is to transform its business and add more digital tools, such as chatbots, but also to make more use of the telematics data largely available given that the Italian telematics car insurance market is one of the largest in Europe. The insurer also plans to use geographic data in combination with weather information to assess the impact on buildings and improve the pricing calculations for property insurance contracts.

While insurance companies are integrating new services and introducing new products to the market, it is important to discuss the potential implications of this increasing data availability.

1.4 The implications of new data usage for the insurance sector

In the present section, we first discuss more general implications of data availability, such as new actors penetrating the market and the ways in which the accessibility of information affects the information asymmetry, characteristic of the insurance market. We further proceed with a discussion on the implications concerning risk classification and risk prevention.

[20] The question was formulated as concerning the "insurance products that would provide a discount based on driving data". The authors of the survey argue that a more direct incentive provided by framing the question as 20% cheaper car insurance had more appeal and lead to the higher proportion of respondents claiming to be interested.

[21] *"Google Solving Together – Generali and the pursuit of digital data democratisation"*, June 19, 2020: https://diginomica.com/google-solving-together-generali-and-pursuit-digital-data-democratisation.

1.4.1 Market structure and the information asymmetry are challenged

As it appears from the discussion provided above, new actors increasingly make concurrence to the incumbent insurers, for two reasons in particular. The access to technologies and data in general, even related to the activities which are not necessarily linked to the insured risks, provides a big advantage to the companies operating in the digital sphere. Consequently, the companies that have access to data due to their specialization in the technological sector start to exert insurance activities as well.

At the same time, it appears less crucial than before to have an established portfolio of policyholders and access to long-term historical data on their risk experience. The advantage of size does not seem to be the factor preventing start-ups from engaging in the insurance activity, in light of the technological capacities allowing them to compete with the incumbent insurance firms.

Therefore, we can distinguish two types of new actors that start to acquire an important share of the market. First, big tech companies, such as Apple, Amazon and Google, are developing their own insurance products. Verily Life Science, a subsidiary firm of Google's parent company Alphabet, is launching this year its insurance company Coefficient, which is reinsured by Swiss Re.

Second, insurtech startups have an increasingly bigger weight in the market. The value of capital invested in insurtech companies worldwide was 13.4 billion U.S. dollars in 2019.[22] Those startups are represented by the *managing general agents*, which are companies associated with the licensed insurers, and by the *full-stack* insurtechs which are independent companies that have their own license to sell insurance contracts.[23] Such independent insurtech companies start to operate in the market, despite the fact that the procedure to receive an insurance license can be a barrier.

Besides, as we mentioned in the introduction, information asymmetry is particularly prevalent in the insurance market. From the theoretical point of view, information asymmetry issues reflect a market inefficiency. On the practical side, insurers employ substantial resources to assess the risks and verify information provided by policyholders (Keller et al., 2018).

[22] According to the survey conducted by Statista: https://www.statista.com/statistics/677817/value-of-capital-invested-in-global-insurance-tech-companies/.

[23] Some examples of full-stack insurtech companies that we mentioned in previous section are Metromile, Lemonade, Luko, One, Alan and Shift Technology.

Adverse selection or moral hazard are less of an issue in certain specific branches of the insurance business. For instance, in branches covering the risks related to construction or natural disasters, the insurers are often considered as better informed about the risk than the policyholders. Due to the specificity of the risks involved, the insurers can produce better estimation and acquire more information than the insured agents, by relying on external expertise in the case of construction insurance or by using sophisticated mathematical models in case of natural hazards.

Nevertheless, in other branches such as property-liability insurance, it is assumed that policyholders have better knowledge of the factors related to their risk because of their characteristics or their actions that are not observable by the insurer. However, given the increasing availability of information and the development of data collection and data treatment techniques, the relation between the insurers and the policyholders in terms of informational advantage becomes less clear-cut.

First, the insurers use multiple analytical tools and rely on computational statistics and actuarial science in order to assess risks. This analytical advantage in estimating risks is not a novelty.[24] Yet, this technical superiority is only strengthened in light of recent technological advances. Second, insurers have access to a bigger quantity of information, both from old and new sources. The cost of acquiring and analyzing standard declarative information decreases, with additional new information on individual behavior becoming accessible.

Since insurers have access to information which is more voluminous and rich, they can, in theory, identify with more precision the individual characteristics relevant for risk assessment, as well as the personal needs of each policyholder. Under the hypothesis of decreasing information asymmetry, which becomes plausible given the context, the information accessibility creates a possibility to build smaller risk classes for price discrimination and segmentation and to provide personalized recommendations on the risk-preventive behavior.

It seems undeniable that the insurance firms and the companies from other sectors operating in the digital and technological sphere have access to more information today than 10 years ago. Only 20% of the world's data can be accessed through the web search, meaning that 80% of the world's collected data is privately owned, mostly by businesses.[25] By taking advantage of the new sources of collected data, the insurers might equalize their position with the policyholders in the principal-

[24]We mentioned before the theoretical work on informed insurers (Villeneuve, 2000) which stems from an observation that insurers can be viewed as experts in their domain, which is risk assessment.

[25]"*We need a new era of data responsibility*", Gini Rometty, Executive Chairman at IBM, for World Economic Forum Annual Meeting, 2018.

agent relationship. The balance, or possibly a reversal of roles in this relationship does not imply that the risk will become perfectly predictable, but only that the insurer might become at least as informed about the relevant characteristics and actions as the policyholder.

In the previous sections, we presented the factual changes in the types and sources of available data. We also provided examples of new actors and new products created as a result of the increased data availability. As it becomes clear, the development of the insurance sector has important potential implications related to the relationship and the interactions between insurers and policyholders, in terms of the way their contractual relationship unfolds.

The possibility of such new configurations calls for a new look at some economic models and hypotheses that can be revisited. This leads us, within the framework of the present thesis, to the examination of a set of possible angles, from which we can analyze the way information asymmetry issues can evolve in the current context.

In particular, given the information availability discussed in the previous sections, we want to address possible implications of insurers being informed about the policyholders' risk types or their preventive effort. These hypotheses are especially interesting in application to the property-liability insurance sector, which is assumed to be particularly subject to information asymmetry issues. Therefore, there are two directions for further discussion that naturally emerge: the implications in terms of risk classification, and the implications in terms of incentives for risk prevention.

1.4.2 Individualization, personalization and risk classification

The segmentation of policyholders by risk classes based on similar characteristics is one of the principles of private insurance. Advanced analytical tools and more detailed data allow, in theory, to move towards more individualized insurance contracts, both in terms of coverage and premium. In particular, one can imagine that insurers will offer personalized services suited to the needs of each policyholder, but also set more risk-adequate premiums by creating more risk groups.

The additional information on individual risks does not necessarily imply better risk estimation. For instance, a pooling premium does not suppose the absence of risk evaluation or that the estimation is inaccurate. The pooling premium represents an averaged price as opposed to the individualized one. Hence, a decrease in pooling in favor of more risk-adequate premiums suppose more classification based on new variables, for example, and therefore less cross-subsidization between different risk types.

Thus, the possibility of increased price differentiation is viewed as a threat to the mutualization principle of risk pooling. The assumption is that the insurers will aim to increase risk segmentation to offer lower premium levels for the low-risk agents. We do not aim to establish whether risk segmentation is good or bad from the ethical point of view, all the more so given that this question is intertwined with a large panel of societal, ethical, and epistemological inquiries. We intend to discuss a part of the possible implications of increased individualization and risk classification.

The main drivers of risk classification are the "fair" prices and competition (Cevolini and Esposito, 2020), which are interlinked in certain ways. From the technical point of view, they are also linked to the *construction* of homogeneity created by subdividing the portfolio into groups of supposedly similar risks (Barry and Charpentier, 2020). "Unfair" prices are related to the cross-subsidization resulting from the risk heterogeneity inside each risk class, which implies that low risks subsidize high risks from the same group. Given the competition in the insurance market, the insurers that do not differentiate risk types will lose their low-risk clients if a competitor offers them more attractive premiums.[26] Nevertheless, the conclusion on the benefits that the insurers could obtain from an increased risk classification is less obvious than it might seem, as we will discuss further in this thesis.[27]

The mere existence of debates around the question of risk classification and individualization attests to the complexity of the subject which extends to other domains outside of the insurance practice. The notion of fairness is itself an intricate notion, with significant divergence between the concepts of social fairness and individual fairness (Cevolini and Esposito, 2020). While cross-subsidization is considered unfair for the low-risk agents, the classification based on any characteristic is inevitably unfair at least to some individuals involved.

Additionally, it is not obvious to state which classification factors are "fair" or "objective". For instance, the European Union authorities prohibit premium discrimination based on gender. Moreover, the insurers must provide actuarial evidence on the relation between risk factors and loss experience. According to Solvency II directive, each trimester the insurers must provide the *Quantitative Reporting Template*, including the information on the models used to determine the risks and calculate

[26] The practice referred to as *cream skimming*.

[27] An interesting illustration of the complexity of the resulting situation is presented by Charpentier, Denuit, and Elie (2015).

the premiums for different branches of activity.[28] To give another example, Belgian law requires explicitly that insurers provide "objective evidence" of the differences in losses between risk groups in order to be able to differentiate prices (Meyers and Van Hoyweghen, 2020).

The focus being on the threat that risk classification represents for the mutualization of risks and the coverage of high-risk agents, it should be noted that even the practical question of *what is* a high risk has no definite answer. For instance, from the technical point of view, it is easier to draw a conclusion about who is a low risk based on claims history data, than to qualify a policyholder as a high risk.[29] It can be argued that only time can allow answering the question on the "true" risk level of any given policyholder, since the evolution of individual history is what brings clarity, partial at least.

Throughout the two following chapters of this thesis, where we adopt a theoretical approach to the question of risk classification and its impact on different risk types, we define high risks as policyholders having a high probability of suffering a loss. Assuming that information is symmetrical due to the data available on individual characteristics and actions, we consider that it is possible to perfectly differentiate risk types. Provided such a possibility, we explore the impact it would have on high and low-risk agents, building on the common idea that insurers would be mainly interested in risk classification to offer lower prices for the low-risk agents.

In particular, we first examine whether it implies that the insurers will not be interested in providing coverage to the high-risk agents (Chapter 2), and second, whether the low-risk agents and the insurers providing individualized premiums will necessarily benefit from this strategy (Chapter 3). We show that neither assumption is consistent in fact. Nevertheless, we want to emphasize that regardless of the arguments we make, risk-adequate premiums *can* make coverage inaccessible or unaffordable for some groups of the population, and specifically for the less wealthy high-risk individuals.

Hence, an increased risk classification can result in the exclusion of some groups from the insurance market, which is a critical societal issue, especially considering that these segments of the population might be those that need coverage the most. It is particularly important given the nature of data that can result in enhanced risk classification. Historically, this type of risk segmentation was based on factors such

[28] Similar aspects concerning risk classification are also monitored by the French Prudential Supervision and Resolution Authority (*ACPR*).

[29] Does a policyholder who had an accident this year have more chances to have an accident in the following year? Regardless of the answer, the further question is what is the causal argument that drives this conclusion.

as place of living, for example, which is not necessarily a deliberate choice under the policyholder's control. Given the data on individual behavior that is accessible today, the price differentiation can be based on the risk behavior instead of factors such as age or geography, as we will discuss below. While it can be considered more objective and relevant for determining risk exposure, it can also depend on the personal situation outside of the policyholder's control or will. For instance, considering UBI contracts, the time of day when the journey is made can depend on working hours, which, in turn, depend on the type of work exerted.

While the discussion on societal issues is important for this topic, it remains outside of the scope of this thesis. Nevertheless, the subject of risk classification and the possibility of adverse effect on some groups of risks leads us to consider mutual insurance and its particular characteristics.

Considering the specificity of mutual insurance as opposed to private stock insurance, the second question related to the risk classification that we address in the present work is the following. Under the assumption that it is optimal for the stock insurers to individualize premiums in order to attract low-risk agents, would stock insurers rule out mutual insurers in the current market? We argue that it is not necessarily the case, and there are situations in which mutual insurers can insure the entire population despite charging the average premium. Of course, in practice, mutual insurers also differentiate risk types and apply risk classification to some extent, yet some classification variables are voluntarily excluded from the price determination.

Some authors suggest that regulators should be more concerned about group-based price discrimination rather than individualized prices based on personal data provided by the policyholder (Acemoglu et al., 2019; Bergemann et al., 2020). In particular, it is argued that data from a particular individual provides insights not only on this individual but also on other individuals with similar characteristics or behavior. Consequently, even those who decide not to share data might be affected by potential negative externalities stemming from the social dimension of the individual data.

It is also argued that insurers cannot hold superior knowledge on risks because they eventually reveal all the relevant information through the offer they make to the policyholders. In this case, an attempt to attract low risks by offering them a premium only slightly lower than the average one provides a signal about the true risk level. This signal makes the information available to all the contracting parties, or even provides negotiating power to the low-risk policyholders. In the extreme case, illustrated by Siegelman (2014), pooling premiums can even be more advantageous for the insurers than individualized ones.

1.4.3 Behavioral data, new contracts and risk prevention

As we argued below, risk classification should not result in aiming to attract only low-risk agents, even if the information is available to differentiate risk types. But more importantly, the new data on individual characteristics and behavior can be used to provide individualized recommendations and advice to the clients or to provide incentives to prevent risk exposure.

Risk prevention is a risk-reducing activity that takes place before the loss occurs (Courbage, Rey, and Treich, 2013). In general, prevention refers to two different mechanisms that are called self-insurance and self-protection, and each refers to one of the underlying elements of risk: the size of potential loss and the probability of potential loss (Ehrlich and Becker, 1972; Berger, 2016). Self-insurance, also called loss reduction, consists in reducing the size of the loss, while self-protection is called loss prevention and consists in reducing the probability of its occurrence.

The availability of data on individual behavior related to the risk promises the development of self-protection tools, because the information on the individual actions becomes accessible, rather than simply on the size of the loss. Previously, we provided examples of companies using behavioral data to offer discounts and nudge policyholders to exert more preventive actions. Here, we want to discuss some possible implications of using behavioral data to promote prevention.

Individual behavior provides information on what is considered to be endogenous risk factors under the policyholders' control. For instance, it seems undeniable that it is ethically correct to prohibit discrimination based on genetics data, even if it is related to the individual characteristics relevant for risk assessment because it is not an individual choice. However, the physical exercises seem to be a good indicator of "hidden action" relevant for estimating the policyholder's risk level.

In the last chapter of this thesis, we adopt an experimental approach to provide insights on some questions stemming from the possibility to encourage preventive activities. For instance, we want to compare two insurance contracts, a behavioral contract with a premium based on the preventive effort and a standard experience-based rating.[30] The main questions that we address are the incentives for prevention and the individual preference regarding one or the other of these two contract types.

[30] Also known as credibility rating or as the bonus-malus system in the French car insurance sector.

The absence of non-ambiguous theoretical results on the optimal preventive effort and risk preferences calls for empirical investigation (Dionne and Eeckhoudt, 1985; Briys and Schlesinger, 1990; Eeckhoudt, Gollier, and Schlesinger, 2011; Denuit, Eeckhoudt, Liu, et al., 2016). Experimental methods allow controlling for individual preferences such as risk aversion and prudence, known to form a complex link with the preventive effort. We also aim to examine whether low risks or high risks would have any definite preference towards behavioral or experience-based premiums. On the one hand, high-risk agents can be interested in behavioral premiums, since they have more chances to experience an accident and to pay a higher price as a result. On the other hand, as it is highlighted by theoretical findings on prevention, the preventive effort is determined not only by the individual loss probability but also by the cost of prevention, the effectiveness of preventive mechanism, and by the individual preferences translated by the utility function.

Would policyholders want their behavior to be determinant of their price, and then, would they want to exchange their personal data for the price decrease? The question is even more daunting if individual behavior is not only a determinant of premium *discounts*, but if the adjustment goes both ways and the premium can increase as well. Currently, only rewards and discounts are allowed by European legislation. Besides, the new data on individual behavior is not replacing the classic actuarial and statistical approaches of price determination but is included in the experience-based risk models as a credibility factor (Denuit, Guillen, et al., 2019). Yet, one can imagine that the price could be entirely based on preventive behavior. That is another reason why we consider experimental methods: to explore the eventuality of premiums fully based on the preventive effort, which do not exist in practice yet.

As we mentioned previously, European insurers must provide actuarial evidence on the relation between risk factors and loss experience in order to use any classification variable for pricing, according to the regulatory requirements. Some insurers launch experimental PHYD insurance programs to collect and analyze data and potentially be able to provide such evidence in the future (Meyers and Van Hoyweghen, 2020). Hence, empirical insurance data on the UBI programs exists already and represents an interesting avenue to explore in order to answer additional questions related to the use of telematics data in insurance.

From the societal perspective, the debate on the difference between two systems, one based on the effort and another on the claims history, can be linked to the discussion on the "objectivity" of risk classification factors that we mentioned previously. On the one hand, it can be perceived as unfair to penalize a policyholder based on the fact that the accident has occurred. The agents buy insurance in the first place to be covered against the risk of an accident. Moreover, it can simply be bad luck and does not necessarily mean that the individual did not exert any preventive effort. On the other hand, to sanction the absence of preventive effort as opposed to the accidents is to judge on something that did not occur (yet), which can also be perceived as unfair.[31]

From the individual point of view, the preference towards one or the other of the contract types can be determined by factors such as risk aversion or prudence, as we will discuss in Chapter 4. It can also be determined by personal psychological or ideological beliefs. Aside from the individual risk level and the monetary incentives provided by premium discounts, one can see the question of the attractiveness of behavioral premiums as the question of preference towards being judged by the outcome or the effort made. In this sense, the debate has some similarities with the concepts of outcome accountability versus process accountability (Patil et al., 2014). It is also close to the discussion on personal ideological preferences behind the choice between stock and mutual insurance, which we will mention at the end of Chapter 3.

While we find important to examine the optimal choice from the theoretical point of view, it is valuable to explore and discuss the underlying beliefs and perception. Although some policyholders might want to exchange their personal data for the decrease in premium, others could be reluctant to provide individual data for privacy and security reasons. Yet, the possibility to provide personal data on relevant behavior (or other relevant characteristics) could lead to the voluntary revelation of information by low-risk policyholders, which could result, in theory, in information unraveling in the sense of Milgrom (1981), which is considered efficient from the theoretical point of view, but can entail distributional consequences (Mimra and Wambach, 2017). The discussion on the use of personal data is an important topic for regulators and policymakers, and will undoubtedly remain as such.

1.5 Conclusion

The new data-rich environment promises a series of improvements: more customization, better tailoring of products, better security, more efficient service, fraud de-

[31] Nevertheless, the telematics data on the accidents that did not occur but were closely avoided, the so-called "near-miss events", gives important information on the risk of being involved in future accidents and on the conditions in which those accidents are likely to occur (time of the day or area). Some authors suggest that such information could be used in setting a personal benchmark for warnings or premium rewards (Guillen et al., 2020).

tection, and the possibility to promote preemptive actions. Therefore, there are benefits in having new data, new techniques of continuous collection of information, greater computational capacity, and new processing tools.

Digital transformation and new data could enable the creation of insurance coverage for risks that were previously uninsured, such as insuring disaster-prone areas with the help of satellite pictures and geographical data (IAIS, 2020). In some cases, it also allows offering more affordable insurance products, due to the decrease in certain costs, as well as more accurate pricing. At the same time, individualization can create a risk to some groups of customers, and regulators should pay attention to the availability and affordability of insurance, especially for the types of coverage that are essential or mandatory.

In this chapter, we discuss how different aspects of the insurance business are modified with access to the new data, in particular regarding the market structure and the insurance products. We provide multiple examples of new actors and new contracts that shape the current state of the insurance market and discuss the applications that data accessibility and new digital tools find in the insurance business. This discussion gives rise to the questions that we aim to address in the rest of this work.

In particular, the possibility to acquire more information on the individual risk types could produce more risk classification and allow to promote preventive actions. These two issues are examined in the last sections of the present chapter. The questions related to these two points will be studied further in the following chapters, namely the impact of risk classification on the high-risk agents (Chapter 2), the impact on the low-risk agents and the attractiveness of stock and mutual insurers (Chapter 3), and, finally, the incentives for prevention provided by the new contracts based on the behavior and the preference for such contracts compared to the standard experience-based ratings (Chapter 4).

Chapter 2

Risk pooling and ruin probability, or why high risks are not bad

This chapter is the basis of the article "*Risk pooling and ruin probability, or why high risks are not bad*", co-authored with Sandrine Spaeter-Loehrer

Summary of the chapter

The aim of this chapter is to address the recently appeared issue of the risk type revelation and the impact it could have on high-risk agents in the insurance sector. We argue that the possibility to identify different risk types and better tailor insurance contracts, provided by recent innovations related to data collection, does not mean that high risks should be dismissed, in particular, because the intention of insuring low risks only can lead to solvency issues. We introduce heterogeneous risks and two types of risk loading in the analysis, because the size, the combination of risk types, and their contribution to the buffer fund through the loaded premiums are the elements that define the insurer's risk and solvency. We show how the insurer's risk and the probability of insolvency are affected by the composition and the size of a heterogeneous insurance portfolio, which must be considered given the legal requirements relative to insurers' insolvency. Moreover, under some conditions, high-risk agents contribute more to the insurer's ability to manage the risk of insolvency. Overall, we argue that the information on the risk types should be used to provide incentives for risk reduction to the agents revealed to be high risks.

Keywords: heterogeneity, information, loading, pooling, solvency

JEL classification: D81, G22, G28

2.1 Introduction

Technological advance produces new means of data generation, new ways of gaining information and new tools for data analysis. All of them may be used by insurers to evaluate individual risk profiles, decrease the uncertainty on risk parameters and incentivize risk prevention and risk reduction. Devices such as fitness trackers or smartphones allow to monitor and encourage healthy physical activity through bonuses or premium reduction. Telematics boxes installed in cars allow to record driving patterns, detect dangerous behavior on the road and provide a basis for the estimation of behavioral premium discounts. Overall, telematics, which brings together data collection and communication, creates a shift towards more personalized insurance based on individual behavior. While important for encouraging risk prevention, it also produces various concerns regarding the use of information.

In particular, one concern that arises from recent innovations in the insurance sector is about the agents who are revealed to be high risks. Today, it is possible to learn more about a policyholder's individual risk level and to discover who is "good" and who is "bad" without owning long series of historical data. Yet, in some insurance newspapers, the notion of a high risk is sometimes confused with the concept of bad risk, although it is not consistent *per se*. Recall that the well-known "lemon market" issue (Akerlof, 1970) arises specifically because of the hidden knowledge: a high risk is not a bad risk, but becomes bad whenever it is impossible to know whether she is one.

On the one hand, new technologies actually allow insurers to attract "good" risks, that is policyholders with a low individual probability of becoming claimants.[1] On the other hand, the possibility to identify different risk types and better tailor insurance contracts does not mean that high risks should be dismissed. First, it is possible to use the information on individual risk factors and behavior to promote preventive actions and reduce the risk level in the high-risk group. Second, it is neither systematically feasible nor desirable for the insurer to build a portfolio including only low-risk policyholders. As it will be shown in this chapter, the insurer's risk and the probability of insolvency are affected by the composition and the size of the insurance portfolio or risk pool.[2] Homogeneous pools that are sufficiently large might be difficult to create, in particular with regard to the increasingly strengthening equity constraints imposed by the regulators. Hence, the intention of insuring

[1]For example, the American insurtech company Root uses smartphones to measure driving behavior. The startup claims to insure only safe drivers and consequently to offer more affordable rates to its clients.

[2]We use those two terms interchangeably through this chapter.

low risks only can lead to size and solvency issues.

In the present chapter, we focus on the stock insurance portfolio heterogeneity with regard to insolvency, and especially on the role of the high-risk policyholders. Considering regulatory perspective, European insurers have to reduce and control their probability of insolvency according to the legal terms of policyholders protection (Solvency II).[3] Its mission is to regulate the European insurance market, enhance its harmonization and improve the policyholders' protection. In order to protect policyholders from insolvency, insurers have to provide a correct evaluation of their risk and form a proper buffer fund, which should be used to maintain the ruin probability under a required level of 0.5% a year.

This chapter provides a perspective on the insurer's point of view given the regulatory requirements regarding the solvency level. In particular, we introduce heterogeneous risks and two types of risk loading in the analysis, because the size, the combination of risk types and their contribution to the buffer fund through the loaded premiums are the elements that define the insurer's risk and solvency. We suggest and show that it is not necessarily desirable for the insurer to form a homogeneous pool of low-risk policyholders, at least from the regulatory perspective. Under some conditions, high-risk agents contribute more than low risks to the insurer's risk-bearing capacity and to the mitigation of the probability of insolvency. Besides, the information on the risk types can be used to promote prevention and risk reduction and incentivize the agents that are revealed to be high risks to lower their exposure.

We analyze the link between the stock insurance portfolio composition, the probability of insolvency, and the risk loading, also known as safety loading, within a one-period model of the insurer's global risk. Loaded premiums enable the accumulation of a buffer fund used to manage the probability of insolvency, and two types of premium loading are considered in the present chapter, the additive loading and the multiplicative one. Given this framework, we consider independent high and low risks and we obtain our results first for binary distributed, and then for normally distributed risks.

More precisely, if the loading is multiplicative and the risks are binary distributed, high-risk agents contribute proportionally more to the buffer fund. Consequently, adding new high-risk policyholders enables a faster decrease of the probability of insolvency. Or, putting differently, if the probability of insolvency is fixed, the pool can be smaller if it is heterogeneous or contains high risks only, compared to

[3]Solvency II is the European Union Directive on the taking-up and pursuit of the business of insurance and reinsurance that came into effect on January 2016.

the homogeneous low-risk pool. When risks are normally distributed, the premium is decreasing with the size of the pool, yet high-risk policyholders do not necessarily enable a faster decrease in the probability of insolvency, because the size of the loss is not fixed. However, the premium size decreases with the high-risk agent's risk level, represented by their claims variance.

Consequently, our results support the idea that the information on the individual risk level will not reduce the level of coverage offered to the high-risk agents. Moreover, it gives an insight regarding the potential to provide incentives for prevention and self-protection, as it will be discussed at the end of this chapter and explored through other chapters of this thesis.

The present chapter is organized as follows. In Section 2.2, we provide a literature review on the insurers' insolvency and risk pooling from three different perspectives, presenting the issue from the policyholder's and the insurer's points of view (Sections 2.2.1 and 2.2.2 respectively), and completing with the regulatory perspective (Section 2.2.3). In Section 2.3, we use a one-period model of the insurer's global risk to analyze the interplay between the heterogeneity of the stock insurance portfolio and the probability of insolvency. We provide two cases: binary distributed and normally distributed risks (Sections 2.3.1 and 2.3.2 respectively), each with an additive and a multiplicative premium loadings. The implications of our analysis are discussed in Section 2.4. Section 2.5 concludes.

2.2 Related literature

The issues we want to address in the present chapter rely on the link between insolvency and the size and composition of the pool. In this section, we provide a brief overview of the related literature. There are three strands of literature relevant to our discussion. The first is related to the risk pooling and the portfolio size from the point of view of the policyholder's utility. The second one approaches risk pooling in relation to the insurer's safety and probability of insolvency. The last one focuses on the regulatory perspective from both sides.

2.2.1 The policyholder's point of view

Risk pooling allows us to reduce possible variations of one's wealth by subdividing the global variance of the pool among all the participants (Borch, 1962). In terms of the size of the pool, the benefits of risk pooling can be described by two possible results of an increase in the pool size. Given an increase in the number of policyholders, it is possible, but not systematically, to either provide a lower price for insurance coverage for the same level of safety determined by the probability of insolvency or to offer a higher level of safety for the same price. Gatzert and Schmeiser (2012) and Albrecht and Huggenberger (2017) revisit those benefits of the risk pooling from the policyholders' perspective.

Gatzert and Schmeiser (2012) question the idea that the benefits of risk pooling, as described above, are inherently advantageous for policyholders. In particular, they show that risk-neutral mutual participants are indifferent about a possible decrease in the premium level following an increase in the pool size. Indeed, a decrease in the premium level in the case of mutual insurance would merely alter the partition between the equity and the debt-holder claims for each participant, which is a distinctive feature of mutual insurance.[4]

The authors also show that mutual participants do not necessarily need an insurer as a financial intermediary if they are able to replicate the contract's cash flows and claims themselves through the financial markets when the latter are complete. Otherwise, the insurer becomes more efficient in diversifying the global risk and provides an additional value to the policyholders.[5] In this case, the benefits of risk pooling are linked to the decreasing risk, following an increase in the number of participants. Finally, the authors mention that in the case of homogeneous risks, the benefits of the mutual pool are unconditional on the premium principle, the latter being defined by the type and the size of the premium loading.

Albrecht and Huggenberger (2017) develop a further analysis of the risk-pooling benefits from a policyholder's perspective. They relax the assumptions used by Gatzert and Schmeiser (2012) and consider no specific distribution for individual risks and no specific form of a utility function, while also extending the results beyond the expected utility theory. Using the idea that individual risks are similar in the sense that they are exposed to the same claims generating mechanisms, the authors show that every increase in the mutual pool size leads to an additional increase in policyholders' utility. Hence, the authors establish a monotonic increase of pooling benefits with the pool size, compared to the traditional results for the large portfolios, which are based on the asymptotic arguments. Indeed, the pooling benefits are generally examined through the law of large numbers and the central limit theorem applied to the infinitely large portfolios so that any additional policyholder always increases those benefits.

[4]Indeed, a particular feature of mutual insurance is that mutual participants are shareholders themselves. Consequently, they are simultaneously entitled to the dividends from a positive surplus and the additional premium payment in case of a negative surplus. This feature will be discussed in Chapter 3.

[5]The value of risk pooling would therefore depend on the policyholders' initial wealth and preferences, such as risk aversion (Borch, 1990).

While being essentially interested in the policyholder's perspective, Albrecht and Huggenberger (2017) admit that the consideration of the insurer's perspective is in line with the common requirements of external regulation. Likewise, despite questioning the merits of pooling claims for the policyholders, Gatzert and Schmeiser (2012) still agree upon the importance of increasing insurer's safety from a regulatory perspective. We, in turn, are interested in the stock insurance case from the insurer's perspective and when risks are heterogeneous. In Section 2.3, we consider a decrease in the stock insurer's global risk following an increase in the size of the portfolio. We also introduce different types of risk loading, which is relevant in the case of a heterogeneous stock insurance portfolio.

2.2.2 The insurer's point of view

Risk pooling is also related to the insurer's risk of ruin, or insolvency.[6] The risk of ruin is the probability that the insurer will not be able to cover all the losses experienced by the policyholders in a given contractual period. The classic treatment of the insurer's risk appears in Houston (1964), where the author presents insurance as a form of a sampling model and describes its functioning through the individual risk theory. Houston (1964) also states the necessity of a buffer fund to cover unexpected losses which are a direct monetary measure of the insurer's risk.

Extending the work started by Houston (1964), Cummins (1974) discusses the use of the central limit theorem in relation to the buffer fund needed to achieve the desired safety level. In particular, Cummins (1974) pinpoints the difference between insurer's absolute and relative risks through the distinction between the buffer fund per policyholder and the total buffer fund. The buffer fund per policyholder is the risk loading added on top of the pure premium. The sum of those individual contributions through the loading forms the total buffer fund which allows accumulating resources needed to manage the insurer's risk. Cummins (1974) shows that the buffer fund per policyholder tends to zero with the size of the pool, yet the total buffer fund needed to insure an infinitely large pool is infinite as well.

Those ideas are further developed in Cummins (1991) where the author discusses the role of the risk loading added on top of the pure premium as a mechanism of mitigation of the insurer's risk of insolvency. Moreover, he emphasizes the fact that homogeneity is not necessary for risk pooling, but for reducing adverse selection.[7]

[6]The risk of insolvency is a more complex notion than the risk of ruin (Powers et al., 2003), the latter being related to the one-period models. Nevertheless, for the sake of simplicity, we use both terms interchangeably.

[7]Indeed, as we previously mentioned in the introduction, what makes a high risk a bad risk is the absence of knowledge concerning the individual risk level.

The author also quotes Feller (1968) to remind that in the case of Bernoulli distribution, the homogeneity increases the variance in the risk pool. He argues that heterogeneity would only increase risk in the situation where the risk types or the proportion of different risk types are not known exactly. This problem is at least partially attenuated in the current context of data availability, and we will consider this property when developing our model in Section 2.3.

The risk loading is an important element for the discussion about the link between the insurer's insolvency and the size and composition of the insurance pool. Indeed, an insurer needs some capital to reduce the probability of insolvency.[8] The risk loading, the size of the pool, and their impact on the ruin probability are well illustrated by M. Smith and Kane (1994). The authors continue the discussion started in Houston (1964) and Cummins (1974) by showing explicitly how the insurance principle works through the application of risk loading. Namely, they discuss its necessity, as well as two possible results following an increase in the size of the pool: a decrease in the safety loading for a given safety level, or an increase in the safety level for a given size of the loading.

M. Smith and Kane (1994) provide a numerical example to illustrate a possible non-monotonicity of the ruin probability function. In particular, the authors show that for small pools, an additional entry can weaken the insurance capacity to cover losses, even with a positive risk loading. This issue is sometimes neglected, the law of large numbers and the central limit theorem being asymptotic statements. In Section 2.3, we will discuss the difficulty to create a homogeneous low-risk pool that is large enough to meet solvency standards. Thus, we will highlight the importance of considering both high-risk and low-risk agents in risk pooling.

The size of the insurance pool alone is certainly not a unique criterion for insurance functioning.[9] Denuit, Eeckhoudt, and Menegatti (2011) state that while adding risks decreases the probability of insolvency, it does not necessarily increase the insurer's utility. Extending previous work on the conditions under which adding risks is beneficial in terms of reducing insurer's risk aversion (Samuelson, 1963; Diamond, 1984), they show that it is not always desirable to accept two portfolios even if the risks are identical and independently distributed in both of them. For instance, the

[8] Some discussion on the central limit theorem and the normal approximation for estimating the ruin probability and the capital needs is provided by Brockett (1983) and Venezian (1983).

[9] Porat and Powers (1999) argue that a large number of individual risks is not necessary for efficient risk mitigation, using an example of captive insurance. Indeed, those special forms of insurance such as captive insurance and mutual insurance have a particular trait of providing risk mitigation even for a small number of participants, as it was mentioned for the mutual insurance in Section 2.2.1. However, as Porat and Powers (1999) point out, in the particular case of captive insurance, the premiums are not determined by the principles of risk pooling but rather by market conditions.

sum of premiums compensating for the insurer's risk-taking in case of two risks is not necessarily higher than the compensating premium for a risk represented by the sum of those two risks.

Powers (2006), in turn, shows in his empirical study that a large number of policyholders does not necessarily bring advantage to the insurer in practice. The author finds no significant relationship between premium volume and the magnitude of the insurer's premium to surplus ratio, the latter reflecting the insurer's financial strength. Powers (2006) argue that the benefits that insurers can obtain through the law of large numbers are presumably counterbalanced by a massive underwriting that includes less-known classes of risks. Hence, the benefits are offset by underwriting "poorer" and badly known risks until the ratio approaches the market average.

These observations highlight the importance of using information that has become available in the light of technological advances to better estimate individual risks, as we argue. They also call attention to the advantage of working with existing policyholders and accompanying them to the increase in risk prevention, instead of simply expanding the portfolio. This point will be discussed in Section 2.4. Moreover, it is important to notice, that these studies do not consider the link between risk pooling, size, and policyholders' heterogeneity. We aim to extend the literature on this point in Section 2.3.

2.2.3 The regulatory approach

The insurers' solvency is regulated by the legislation in order to protect policyholders from the non-payment of claims. The solvency issue is therefore important both from the policyholders' and the insurers' perspectives.

One of the early instances of discussion related to the solvency regulation is provided in Venezian (1984). First, the author shows that pooling of independent non-identical risks increases financial efficiency through a higher solvency level, both for the insurer and the insured individuals.[10] However, the author emphasizes other important issues, such as the distributional equity issue, which arises in particular when the loading is not proportional to the expected loss, or the impact of insolvencies on society as a whole. Namely, the author calls attention to the fact that considering efficiency only as a low probability of insolvency undermines the importance of the potential impact that insolvency can have on the policyholders and society in general. Since insolvencies of large insurers, even if highly improbable,

[10]In his setting, Venezian (1984) defines heterogeneous risks as non-identical risks such as in cases of fire versus liability risks, buildings of different values, or different limits of coverage.

can be truly devastating, they have a higher impact on society than the insolvencies of small insurers, and therefore should be regulated accordingly. From this point of view, the author concludes that pooling through one big insurer might be less desirable than having multiple small insurers.

Regulatory requirements concerning solvency aim to increase policyholders' protection by controlling the insurers' probability of insolvency, as the European Union does through the Solvency II Directive. However, Lorson et al. (2012) question the benefits of such regulation for the policyholders. The authors compare the policyholder's willingness to pay for a higher safety level — the former being modeled from empirical survey data provided in Zimmer, Schade, et al. (2009) — with the estimated costs of introducing the Solvency II Directive. They conclude that the costs outweigh the benefits.

Eckert and Gatzert (2018) also consider the policyholders' willingness to pay, associated with risk sensitivity, in deriving the insurer's target level of the probability of insolvency. Those elements are shown to be crucial for the shareholders' value as well, and also relevant outside the firm, given that insurers have to provide the information on their solvency status as prescribed by Solvency II.

In a similar vein of questioning, F. Klein and Schmeiser (2018) explore the relationship between the probability of insolvency and the policyholders' willingness to pay for insurance. Indeed, empirical and experimental research on probabilistic insurance, that is the insurance with a positive probability of a non-payment of claims (Wakker et al., 1997; Zimmer, Schade, et al., 2009; Zimmer, Gründl, et al., 2018), shows that the policyholders' willingness to pay for such coverage is decreasing with a decreased safety level if the policyholders are aware of that. Given that policyholders nevertheless ignore variations of safety level if insolvency is highly improbable and overweight it otherwise (Kahneman and Tversky, 1979), F. Klein and Schmeiser (2018) show that the insurer has incentives to increase the probability of insolvency to the value determined by the policyholders' sensitivity threshold.[11] The insurer has no incentives for further increase because of the policyholders' probability overweighting, but also because of Solvency II requirements.

In Section 2.3, we focus on the stock insurer's perspective in providing a fixed level of the probability of insolvency. Hence, we consider a regulatory context in the spirit of Solvency II. The stock insurer has to evaluate his risk and form a proper buffer fund in order to maintain the ruin probability under a required level. Recall that we are considering heterogeneous risks, thus extending some results mentioned

[11]For that reason, insurers have no personal incentives to make the information on the probability of insolvency more transparent and available for the policyholders.

above and obtained for homogeneous risks. Precisely, we analyze the link between the stock insurance portfolio composition, the safety loading, and the probability of insolvency in a one-period model. We examine independent high and low risks with, first, a binary distribution and, second, a normal loss distribution. We then discuss the high-risk agents' contribution to the insurer's risk-bearing capacity, as well as the potential use of the information on the risk types.

2.3 Probability of insolvency and high-risk agents

To analyze the link between the stock insurance portfolio composition, size, loaded premiums and probability of insolvency, we consider that the insurer's risk of insolvency is represented by the risk of ruin in the following one-period model.

We assume that the population is heterogeneous, and each agent can either be a high-risk type (h) or a low-risk type (l). We will consider two risk distributions, a binary distribution and a continuous distribution.

Each agent can cover his risk of loss by signing a contract with an insurance company. The size of the insurance pool is denoted by $n, n \in \mathbb{N}$. We denote by n_h the number of high-risk agents, and by n_l the number of low-risk agents in the insurance pool, $n = n_h + n_l$, $n_h, n_l \in \mathbb{N}$. Let θ denote the proportion of high-risk agents in the pool, $\theta \in [0, 1]$. Hence, there are $\theta n = n_h$ high-risk agents and $(1 - \theta)\, n = n_l$ low-risk agents in the pool.

Individual heterogeneous risks are assumed to be independent. A high risk is represented by a random variable X_i, $i = 1, ..., n_h$, and a low risk is represented by a random variable Y_j, $j = 1, ..., n_l$. Their distributions will be defined in the following subsections. Thus, the global risk in the high-risk and low-risk group respectively is represented[12] by

$$X = \sum_{i=1}^{n_h} X_i \,, \tag{2.1}$$

and

$$Y = \sum_{j=1}^{n_l} Y_j \,. \tag{2.2}$$

The insurance coverage is purchased by paying an insurance premium, which is calculated on the basis of the individual expected loss. This base insurance premium

[12]Note that the presentation used in equations (2.1) and (2.2) is different from writing $n_h X_h$ or $n_l Y_l$, with X_h and Y_l denoting the individual high and low risks respectively. Despite the fact that all the high (or low) risk agents are identical, such a notation would represent an increase in risk severity rather than a sum of individual risks: it would imply two possible outcomes, while the sum of n individual risks implies $n + 1$ possible outcomes, depending on the number of claimants.

level is called a pure premium. We assume that the insurer charges an additional payment on top of the pure premium in order to manage his probability of insolvency as it will be explained below.

The policyholders' contribution to the insurer's risk-bearing capital takes form of a loading applied to the pure insurance premium. Such a loading is called a safety or a risk loading. Hence, the size of the individual insurance premium is determined by the individual risk level and the loading size, while the structure of the individual insurance premium is determined by the loading type.

We consider two types of insurance premium loading: the additive and the multiplicative safety loadings. The additive loading consists in adding a fixed amount to the pure premium. The multiplicative loading consists in multiplying the pure premium by a fixed factor. Let C denote the additive loading, and c the multiplicative loading rate.

We denote by π_i the individual premium level for a high-risk policyholder i and π_j the individual premium level for a low-risk policyholder j. For simplicity, since we have only two types of independent and otherwise identical policyholders, we can further denote by π_h and π_l the high and respectively low risk premium levels.

For an additive loading C, the high-risk and low-risk agents' insurance premiums are given respectively by

$$\pi_i = \mathbb{E}(X_i) + C \equiv \pi_h\,, \quad \forall i = 1, ..., n_h\,, \tag{2.3}$$

$$\pi_j = \mathbb{E}(Y_j) + C \equiv \pi_l\,, \quad \forall j = 1, ..., n_l\,. \tag{2.4}$$

For a multiplicative loading rate c, the high-risk and low-risk agents' insurance premiums are given respectively by

$$\pi_i = (1 + c)\mathbb{E}(X_i) \equiv \pi_h\,, \quad \forall i = 1, ..., n_h\,, \tag{2.5}$$

$$\pi_j = (1 + c)\mathbb{E}(Y_j) \equiv \pi_l\,, \quad \forall j = 1, ..., n_l\,. \tag{2.6}$$

Finally, let Π denote the sum of the premiums collected by the insurer. Since the insurance premiums are scalars, identical for all agents of the same type, the total premium writes

$$\Pi = n_h\pi_h + n_l\pi_l\,. \tag{2.7}$$

In particular, if we denote Π^a and Π^m the total premium amount with an additive and a multiplicative loadings respectively, we have:

$$\Pi^a = n\Big[\theta\mathbb{E}(X_i) + (1-\theta)\mathbb{E}(Y_j)\Big] + nC \tag{2.8}$$

$$\Pi^m = n\Big[\theta\mathbb{E}(X_i) + (1-\theta)\mathbb{E}(Y_j)\Big] + nc[\theta\mathbb{E}(X_i) + (1-\theta)\mathbb{E}(Y_j)\Big] \tag{2.9}$$

In the following subsections, we will use special cases of these expressions depending on the particular risk distribution under consideration.

Given the total premium Π, the insurer's probability of insolvency writes

$$q = \Pr\Big(X + Y > \Pi\Big). \tag{2.10}$$

The stock insurer has to guarantee a fixed level of the probability of insolvency according to the regulation, such as Solvency II. In our model, we assume that the required level is achieved by constituting a buffer fund formed by the risk-bearing capital. Given that we are interested in extending some previously mentioned results on the homogeneous risks to the heterogeneous risks and in analyzing the role of the high-risk agents, we include in our analysis the impact of the premium principle on the insurer's probability of insolvency. Further, we focus on two probability distributions that we use to examine the link between the stock insurance portfolio composition, the safety loading and the probability of insolvency.

We first consider that risks are binary distributed. Binary distribution, such as Bernoulli distribution, is a simple and instructional way of modeling the risk of having an accident.[13] Then, we proceed with the normal distribution case. It can represent losses of different severity (common in property-liability insurance), and is overall easier to manipulate for technical reasons. It is often used in the literature under the assumption of sufficiently big portfolios and is therefore an interesting case to consider in order to compare our observations to the literature.

2.3.1 Binary distribution

In this section, we assume that each agent is facing a risk of losing a monetary amount L. Thus, individual risks are independent and binary distributed, such that $X_i \sim Bern(p_h)$ and $Y_j \sim Bern(p_l)$, with $p_h > p_l$. The expected loss in this case is given by $\mathbb{E}(X_i) = p_h L$ and $\mathbb{E}(Y_j) = p_l L$, and the insurance premium with an

[13] It can be useful to represent the risk of burglary or theft, for example. While other distributions, such as Poisson distribution, are generally used to model the number of claims, considering that multiple accidents are possible in the given year, Bernoulli distribution is still the simplest way to model the risk of having an accident.

additive loading, introduced by Eq. (2.3) and Eq. (2.4), writes

$$\pi_k = p_k L + C\,, \quad k = h, l. \tag{2.11}$$

Since the insurance premiums are scalars, the total premium denoted by Π^a for an additive loading writes

$$\begin{aligned}\Pi^a &= n_h(p_h L + C) + n_l(p_l L + C)\\ &= \Big(\theta p_h + (1-\theta)p_l\Big) nL + nC\\ &= n\Big[\Big(\theta p_h + (1-\theta)p_l\Big)L + C\Big]\,.\end{aligned} \tag{2.12}$$

For a multiplicative loading, the individual premium introduced by Eq. (2.5) and Eq. (2.6) writes

$$\pi_k = (1+c)p_k L\,, \quad k = h, l\,, \tag{2.13}$$

and the total premium denoted by Π^m writes

$$\begin{aligned}\Pi^m &= n_h(1+c)p_h L + n_l(1+c)p_l L\\ &= \Big(\theta p_h + (1-\theta)p_l\Big) nL + \Big(\theta p_h + (1-\theta)p_l\Big) nLc\\ &= n(1+c)\Big(\theta p_h + (1-\theta)p_l\Big)L\,.\end{aligned} \tag{2.14}$$

Our first result is summarized hereafter.

Result 2.1. *Consider a binary distribution of individual risks. A high-risk agent provides:*

i) the same amount of risk-bearing resources as a low-risk agent when the risk loading is additive;

ii) a higher amount of risk-bearing resources when the risk loading is multiplicative.

For point *i*), note from Eq. (2.12) that the total amount of buffer fund resources depends only on the size of the pool n when the loading is additive. Indeed, the additive loading is independent of the individual risk level, and both high-risk and low-risk agents contribute the same amount C to the buffer fund. At the same time, for point *ii*), note that the multiplicative loading rate is proportional to the pure premium, and, as a consequence, the high-risk policyholders contribute proportionally more than the low-risk policyholders to the buffer fund, as it can be seen from Eq. (2.14).

When the risks are binary distributed, a multiplicative loading results in the high-risk agents contributing proportionally more to the buffer fund than the low-risk agents (Result 2.1), which also results in the following observation.

Proposition 2.1. *Consider a binary distribution of individual risks and a multiplicative loading. Adding new high-risk policyholders enables a faster increase of the buffer fund, compared to adding new low-risk policyholders.*

Hence, it is not necessarily desirable for the insurer to build a portfolio including only low-risk policyholders. The possibility to identify different risk types and better tailor insurance contracts does not mean that high risks should be dismissed.

Result 2.1 describes the impact of loading structure on the risk-bearing capital. We can also note the straightforward impact of the loading size on the total premium amount. Naturally, an increase in either additive loading C or a multiplicative loading rate c enables a faster accumulation of risk-bearing capital. Hence, the size of the risk loading, regardless of its structure, positively affects the speed of funds accumulation.

Further, an increase in the buffer fund leads to the decrease in the probability of insolvency. Other things being equal, when the loading is multiplicative, both a high-risk pool and a heterogeneous pool result in a higher buffer fund than the low-risk pool, and in the lower probability of insolvency. Stated differently, when the loading is multiplicative and the desired level of the probability of insolvency is fixed, less policyholders are required to achieve the latter if the pool is heterogeneous than if the pool contains low-risk agents only.

Proposition 2.2. *Consider a binary distribution of individual risks and a multiplicative loading. A heterogeneous pool of smaller size is required to reach the desired level of the probability of insolvency, compared to the required size of a homogeneous low-risk pool.*

Consequently, mixed pools might be preferred both from the insurer's and the policyholders' point of view. For example, if the data availability enables insurer to detect different risk types, he can use this information to build the optimal combination of policyholders such that the required level of safety is achieved, as it will be discussed in Section 2.4.

Despite the fact that it does not change the observations stated above, it should be noted that in case of a binary distribution, the probability of insolvency decreases non monotonically with size. Indeed, when the loss amount is the same for everyone, as it is the case when risks are binary distributed, additional policyholders increase the global risk and the ruin probability until enough resources are accumulated to cover one additional loss.[14] Thus, an increase in the number of policyholders eventually produces a decrease in the probability of insolvency, but not with each and every new policyholder. This result regarding the non monotonicity of the probability of insolvency in case of heterogeneous risks is an extension of the results provided by M. Smith and Kane (1994) for the homogeneous binary distributed risks.

Note also that regardless the loading type (additive or multiplicative), the amount C and the rate c can be adjusted so that the probability of insolvency is at the same level under either principle. Indeed, given that the probability of insolvency, as it appears in Eq. 2.10, is determined by the global risk and the aggregate contribution of both risk groups, the loadings C and c can be chosen such that the aggregate premium is identical for both loading structures. The adjustment can be calculated by equalizing (2.12) and (2.14):

$$C = c\Big(\theta p_h + (1-\theta)p_l\Big)L\,. \tag{2.15}$$

At the same time, the loading type affects the share of the total buffer fund provided by a given risk group. Hence, the loading type reflects the distributional equity between the policyholders of different risk groups, with multiplicative loading considered more “fair”.[15] Consequently, even if it is possible to achieve the same level of the probability of insolvency with either loading type, the multiplicative loading can be preferred in order to set a proportional contribution depending on the individual risk level.

In the context mentioned above, a high-risk pool allows to reach a higher level of solvency compared to the pool of low-risk policyholders. Stated differently, the same level of the probability of insolvency can be achieved with a heterogeneous or

[14]The probability of insolvency drops when the resources expand enough to cover an additional loss, i.e. when there is an increase in the number of losses that a given pool is able to cover. More details on this result are provided in the Appendix A.1.

[15]However, insurers can decide to omit some information that can be used for price discrimination for some risk groups, as it is sometimes the case in the mutual insurance sector. For example, young drivers are considered to be high risks compared to more experienced drivers, but some mutual insurance companies choose to omit this factor in pricing. Some elements of discussion regarding the concept of fairness in insurance pricing are provided in Chapter 1.

a high-risk pool of smaller size, compared to the homogeneous low-risk pool. The question is whether this result is due to the nature of binary distributed risks, in particular to the assumption of identical amount of loss. We address this question in the next subsection by considering normally distributed risks.

2.3.2 Normal distribution

Suppose that individual risks are independent and normally distributed both in high-risk and low-risk groups. We denote $\mathbb{E}(X_i) = \mu_i$ and $Var(X_i) = \sigma_i^2$ and we can write $X_i \sim N(\mu_i, \sigma_i^2)$ the normally distributed claim size of risk i. In the same manner, we write $Y_j \sim N(\mu_j, \sigma_j^2)$. Given that $X = \sum_{i=1}^{n_h} X_i$ and $Y = \sum_{j=1}^{n_l} Y_j$, as introduced by equations (2.1) and (2.2), the sum of normally distributed random variables is also normally distributed. Hence we have

$$X \sim N(\sum_{i=1}^{n_h} \mu_i, \sum_{i=1}^{n_h} \sigma_i^2) \tag{2.16}$$

and

$$Y \sim N(\sum_{j=1}^{n_l} \mu_j, \sum_{j=1}^{n_l} \sigma_j^2)\,. \tag{2.17}$$

We denote by S the global risk in the pool, $S = X + Y$, which is normally distributed as well. The global expected loss is equal to $\mu_S = \sum_{i=1}^{n_h} \mu_i + \sum_{j=1}^{n_l} \mu_j$. Since the expected loss is the same for all the agents of the same risk type, and it is a scalar, we can write $\sum_{i=1}^{n_h} \mu_i = n_h\mu_h$ and $\sum_{j=1}^{n_l} \mu_j = n_l\mu_l$. Therefore, we have $\mu_S = n_h\mu_h + n_l\mu_l$. In the same manner, given that the global risk in the pool is the sum of independent individual risks, the variance of the pool is the sum of the individual variances: $\sigma_S^2 = \sum_{i=1}^{n_h} \sigma_i^2 + \sum_{j=1}^{n_l} \sigma_j^2 = n_h\sigma_h^2 + n_l\sigma_l^2$. Finally, we have $S \sim N(\mu_S, \sigma_S^2)$, with $\mu_S = n_h\mu_h + n_l\mu_l$ and $\sigma_S^2 = n_h\sigma_h^2 + n_l\sigma_l^2$.

For an additive loading C, the individual premiums π_h and π_l are given by Eq. (2.3) and Eq. (2.4). Hence, the aggregate premium Π^a writes:

$$\begin{aligned}
\Pi^a &= n_h\pi_h + n_l\pi_l \\
&= \sum_{i=1}^{n_h} \Big(\mathbb{E}(X_i) + C\Big) + \sum_{j=1}^{n_l} \Big(\mathbb{E}(Y_j) + C\Big) \\
&= \sum_{i=1}^{n_h} \mu_i + \sum_{j=1}^{n_l} \mu_j + nC \\
&= n_h\mu_h + n_l\mu_l + nC
\end{aligned}$$

$$= \mu_S + nC\,. \tag{2.18}$$

For a fixed probability of insolvency $\overline{q}$, the insurer chooses the size of the premium loading depending on the size of the pool: $C = C(n)$. Then, the probability of insolvency given by Eq. (2.10) can be written as

$$\begin{aligned}\overline{q} &= \Pr\Big(S > \Pi^a\Big)\\ &= \Pr\Big(S > \mu_S + nC(n)\Big)\,.\end{aligned} \tag{2.19}$$

Given Φ the cumulative distribution function of the standard normal distribution, we can rewrite Eq. (2.19) as

$$\begin{aligned}\overline{q} &= 1 - \Pr\Big(S < \mu_S + nC(n)\Big)\\ &= 1 - \Phi\left(\frac{\mu_S + nC(n) - \mu_S}{\sigma_S}\right)\\ &= 1 - \Phi\left(\frac{nC(n)}{\sigma_S}\right)\,.\end{aligned} \tag{2.20}$$

Since $\sigma_S = \sqrt{\sigma_S^2} = \sqrt{n_h\sigma_h^2 + n_l\sigma_l^2}$, we can further rewrite Eq. (2.20) as

$$\overline{q} = 1 - \Phi\left(\frac{nC(n)}{\sqrt{n_h\sigma_h^2 + n_l\sigma_l^2}}\right)\,. \tag{2.21}$$

Let us denote $z_{1-\overline{q}}$ the $(1-\overline{q})$-th quantile of the standard normal distribution.[16] We obtain

$$\Phi\left(\frac{nC(n)}{\sqrt{n_h\sigma_h^2 + n_l\sigma_l^2}}\right) = 1 - \overline{q}\,, \tag{2.22}$$

and therefore

$$\frac{nC(n)}{\sqrt{n_h\sigma_h^2 + n_l\sigma_l^2}} = z_{1-\overline{q}}\,. \tag{2.23}$$

[16]The quantile function of a distribution is the inverse of the cumulative distribution function. Hence, for any cumulative distribution function $F_X(x)$, the p-th quantile denotes the value x such that $\Pr(X \leq x) = p$.

Consequently, the loading $C(n)$ writes:

$$\begin{aligned}
C(n) &= z_{1-\overline{q}} \frac{\sqrt{n_h \sigma_h^2 + n_l \sigma_l^2}}{n} \\
&= z_{1-\overline{q}} \frac{\sqrt{\theta n \sigma_h^2 + (1-\theta) n \sigma_l^2}}{n} \\
&= z_{1-\overline{q}} \frac{\sqrt{n\Big(\theta(\sigma_h^2 - \sigma_l^2) + \sigma_l^2\Big)}}{n} \\
&= z_{1-\overline{q}} \sqrt{\frac{\Big(\theta(\sigma_h^2 - \sigma_l^2) + \sigma_l^2\Big)}{n}} \,. \qquad (2.24)
\end{aligned}$$

Hence, the additive loading depends on the size of the insurance portfolio, the proportion of the high-risk agents, the distribution of risks and the distance between risk types in terms of individual variance.

For the multiplicative loading, the individual premiums are given by Eq. (2.5) and Eq. (2.6). Then, the aggregate premium Π^m writes $\Pi^m = (1+c)\mu_S$. Following the same mathematical reasoning as the one presented above, we have

$$\Phi\left(\frac{c(n)\mu_S}{\sqrt{n_h \sigma_h^2 + n_l \sigma_l^2}}\right) = 1 - \overline{q} \,, \qquad (2.25)$$

and we can write the loading $c(n)$ as follows:

$$c(n) = z_{1-\overline{q}} \frac{\sqrt{n\Big(\theta(\sigma_h^2 - \sigma_l^2) + \sigma_l^2\Big)}}{\mu_S} \,. \qquad (2.26)$$

Finally, given that $\mu_S = n_h \mu_h + n_l \mu_l$, we can rewrite Eq. (2.26) as

$$c(n) = z_{1-\overline{q}} \frac{\sqrt{\theta(\sigma_h^2 - \sigma_l^2) + \sigma_l^2}}{\sqrt{n}\Big(\theta \mu_h + (1-\theta)\mu_l\Big)} \,. \qquad (2.27)$$

We can show that the safety loading and thus the premium size decrease systematically with the number of policyholders in the normal distribution case if the composition is not affected through the proportion θ of high-risk agents. Let us denote $A = \theta(\sigma_h^2 - \sigma_l^2) + \sigma_l^2$ and $B = \theta\mu_h + (1-\theta)\mu_l$. Given Eq. (2.24) and Eq. (2.27), we can write $c(n) = \frac{1}{B}C(n)$. With θ fixed, we have:

$$\frac{dC(n)}{dn} = -\frac{1}{2n^2} z_{1-\overline{q}} \sqrt{nA} \ < \ 0 \tag{2.28}$$

$$\frac{dc(n)}{dn} = -\frac{1}{2n^{\frac{3}{2}}} z_{1-\overline{q}} \frac{\sqrt{A}}{B} \ < \ 0 \tag{2.29}$$

It also decreases with a reduction in the risk level of the high-risk agents. By denoting $D_{\sigma^2} = \sigma_h^2 - \sigma_l^2$, we have:

$$\frac{dC(n)}{d\sigma_h^2} = \theta \frac{1}{2n} z_{1-\overline{q}} \left(\frac{1}{n}(\theta D_{\sigma^2} + \sigma_l^2)\right)^{-\frac{1}{2}} \ > \ 0 \tag{2.30}$$

$$\frac{dc(n)}{d\sigma_h^2} = \theta \frac{1}{2\sqrt{n}B} z_{1-\overline{q}} (\theta D_{\sigma^2} + \sigma_l^2)^{-\frac{1}{2}} \ > \ 0 \tag{2.31}$$

In the normal distribution case, the size of the loss can take an infinite number of values. Hence, we do not observe the same result as with a binary distribution. Indeed, the probability of insolvency is not necessarily lower in the high-risk pool. Nevertheless, for a fixed level of probability of insolvency, the premium is decreasing with the size of the pool, if the proportion of high-risk and low-risk agents is not affected. Additionally, the premium decreases with the risk level of high-risk agents, represented by their claims variance. These observations and their implications will be discussed in the next section.

2.4 Discussion

The insurer's risk of ruin is subject to regulation. According to the legal requirements, insurers are bound to control their risk of ruin in order to conform to the policyholders' protection terms. In Europe, those terms are currently set within the framework of Solvency II.[17] According to this directive, insurers must be in line with the Solvency Capital Requirement, which is the amount of capital to be held in order to ensure an acceptably high level of financial safety.[18]

In this chapter, we choose to focus on the solvency issues from the insurer's point of view exclusively. We know that the probability of insolvency does not represent the only matter of importance in insurance functioning. Indeed, a low level of

[17] In the United States, the insurance regulation is primarily delegated to the states. Solvency standards, including risk-based capital requirements, are established by the National Association of Insurance Commissioners (NAIC) consisting of the chief insurance regulatory officials in each state (R. Klein, 2012).

[18] The latter corresponds to the probability of solvency of 99.5% over twelve months, thus limiting the chance of ruin to less than once per 200 years.

the probability of insolvency does not imply that the possibility of insolvency is excluded: while the probability of insolvency can be very low, its potential impact can be huge.[19] Consequently, it is important to go further and take into account the effect that insolvency can have on the policyholders.

In particular, if the insurer is insolvent, some policyholders will not receive their coverage and are thus directly affected by the recovery rate, which represents the part of the compensation that can be recovered in the event of the insurer's default. In Chapter 3, we will incorporate the possibility of partial coverage resulting from the insurer's insolvency in our analysis of the choice of insurer, mutual or stock, given that the policyholders are affected differently by the insolvency depending on the insurer's type.

Another aspect regarding this perspective is the policyholders' willingness to pay, given that the solvency constraints imposed on the insurers can represent a regulatory burden translated onto the policyholders through higher prices. The difficulty to create a sufficiently big insurance pool to comply with the regulation requirements can be compensated by higher premiums for the existent policyholders.

On the one hand, an increase in premium level might exclude some groups of high-risk agents from the insurance market. Without subsidization from the low-risk policyholders, the risk-adequate premium can make insurance coverage difficult to afford for the less wealthy high-risk agents. It is undeniably an important societal issue that must be addressed but remains outside of the scope of this thesis.

On the other hand, a crowding out of a proportion of high-risk policyholders can deteriorate the insurer's coverage capacity and consequently neutralize a risk-adequate decrease in premiums for the remaining low-risk policyholders. Thus, surprisingly, high risks' eviction can in theory have an adverse effect and is not necessarily desirable from the insurer's point of view, since the crowding-out of high-risk agents can trigger the crowding-out of low-risk policyholders as well.[20]

Nevertheless, the probability of insolvency remains an important issue due to the regulatory requirements. If the insurers must conform to the solvency standards, as is the case with the Solvency II Directive, they are bound to achieve a required level of safety by maintaining the probability of insolvency at the specified level. The required safety level in our setting can be achieved by choosing an appropriate risk loading or by expanding the size of the pool.

[19] Denuit, Eeckhoudt, and Menegatti (2011) pinpoint the fact that the total payout is as important for the insurer as the average loss per policy. Hence, while risk pooling might decrease the probability of insolvency, increasing the size might as well increase the risk of a large loss. Following Brockett (1983), the authors also argue that calculating the ruin probability of an increasing number of risks is a large deviation problem.

[20] This point is also addressed in Chapter 3.

It is not always feasible for the insurer to gather a pool of low-risk policyholders large enough to achieve the required level of probability of insolvency. Given the interplay between the size of the pool, the premium level and the probability of insolvency, maintaining the homogeneity in the low-risk pool might, in this case, lead to the rise in the premium level for the low-risk policyholders, compared to the mixed pool setting. Hence, mixed pools might be preferred both from the insurer's and the policyholders' points of view. Moreover, if the data availability enables the insurer to detect different risk types, he can as well establish the optimal combination of policyholders given their risk type, such that the required level of safety is achieved, or that any further increase in size maintains the ruin probability below a target level.

This implication is particularly important for the new insurance firms that are more vulnerable to the variations of the number of clients. For instance, the insurtech start-up companies might find it difficult to gather enough policyholders from the launching of their business. Consequently, in practice, they are often affiliated with the big insurers with an established portfolio. It is also important for the insurance sectors with a limited number of potential policyholders, as it is the case for the insurance against specific risks or artisans liability insurance. Indeed, if an insurance pool is already below the requirements concerning the ruin probability, the insurer can accept variations of his portfolio size, which may not be the case if his portfolio is small.

The size of the insurance companies is in fact another issue that should be mentioned. Solvency constraints aim to protect policyholders, yet, as can actually be observed in the insurance sector, solvency constraints also push some insurers to merge.[21] While it might seem efficient from the point of view of capital accumulation, it is not necessarily the case in the light of the potential effects of insurers' failure. Merging enables the capital accumulation and lowers the probability of insolvency, yet this probability is still positive. In the case of insolvency, in particular, due to the systemic risk (natural catastrophes, global pandemics, or cyber-attacks), big insurers' failures would imply more losses since more clients would be affected. In this context, merging and concentration will make the impact of insolvency much more prominent, assimilated to what the world has encountered with the financial market crashes in recent years. From the society's point of view, insolvencies of small and large insurers do not have the same global impact, since failures of big companies loom large due to their geographical or societal reach.

[21] In 2021, two big French mutual insurers Macif and Aésio have announced their merging. In the health sector, the newly created group VYV includes multiple mutual insurers such as Harmonie mutuelle, MGEN, and some others.

Current improvement in information accessibility can provide a tool for restoring distributional equity issues, which have persisted regardless of competition in the insurance markets due to the scale economies and the lack of information. But more importantly, it allows the insurers to focus on the applications of the information availability to promote preventive activities. Relying on the better-tailored insurance contracts with an emphasis on self-protection seems to be important compared to the increase in size in order to exploit asymptotic properties and other purely statistical benefits, or attract exclusively low-risk agents. Information can allow decreasing the individual risk level through the changes in risk factors that are endogenous, such as efforts made to manage the risk exposure. We address this point in Chapter 4.

2.5 Conclusion

Following the expansion and the availability of new data on the individual risks, questions arise concerning high-risk policyholders. In this chapter, we argue that the agents that are revealed to be high risks and the new low-risk policyholders are equally important for the insurer from the point of view of solvency constraints. Not only the size and the individual risk level but also the combination of risk types and their contribution to the buffer fund are the elements defining the insurer's risk and solvency.

We introduce heterogeneous risks and two types of risk loading in the analysis, in order to take into account the size, the combination of risk types, and their contribution to the buffer fund through the loaded premiums. Loaded premiums enable the accumulation of a buffer fund used to manage the probability of insolvency, and we consider both the additive and the multiplicative risk loadings. Given this framework, we consider independent high and low risks and we obtain our results first for binary distributed, and then for normally distributed risks. We show that it is not necessarily desirable for the insurer to form a homogeneous pool of low-risk policyholders, at least from the regulatory perspective. In some cases, high-risk agents contribute proportionally more to the mitigation of insolvency, compared to low-risk agents.

From the policyholders' point of view, it is important to consider not only the probability but also the impact of insurers' insolvency. Indeed, if the insurer is insolvent, the resulting coverage will be only partial. We consider this dimension in the following chapter, where we discuss the implications that partial coverage has on the optimal choice of the insurer's type for a heterogeneous population of agents seeking to insure their risk.

Besides, as we have shown in the present chapter, the high-risk agents are important as well, and their impact on the insurer's probability of insolvency can be managed. In particular, the information on the risk level and the related elements can be used to promote prevention and risk reduction and provide incentives for lowering the risk exposure to the agents that are revealed to be high risks. Those new possibilities have to be considered as an opportunity to improve the insurance business, the contracts, and the services, both for policyholders and the providers of insurance. We will examine the new type of insurance contracts that include the information on the individual behavior and their potential to encourage risk prevention activities in Chapter 4.

Appendix A

A.1 Non-monotonicity of the ruin probability in case of binary distributed claims

When risks are binary distributed, the number of individual payments (premiums) required to cover one loss is equal to $\hat{n} = \{n \mid \theta n \pi_h + (1-\theta) n \pi_l = L\}$. Hence, the minimum number of policyholders required to cover one loss is equal to $\overline{n} = \min n \in \mathbb{N} \mid \theta n \pi_h + (1-\theta) n \pi_l \geq L$,. In other words, if $\hat{n}$ is the number of individual payments required to cover exactly one loss, then $\overline{n}$ is the number of policyholders required to provide the necessary amount of premiums: $\overline{n} = \lceil \hat{n} \rceil$. It is therefore the minimum pool size required to achieve the capacity to cover one loss.

The minimum pool size $\overline{n}$ required to cover one loss depends on the pool composition: multiple combinations of high and low risks provide the necessary amount of the risk-bearing capital. For instance, for a given number of high-risk policyholders $\overline{n}_h$, the minimum pool size $\overline{n}$ is given by $\overline{n}$ such that

$$\overline{n} = \left\lceil \frac{L - \overline{n}_h \left(\pi_h - \pi_l\right)}{\pi_l} \right\rceil ,$$

and the premium quantity required to cover exactly one loss is $\hat{n} = \overline{n}_h + \hat{n}_l$, with $\hat{n}_l$ such that $\overline{n}_h \pi_h + \hat{n}_l \pi_l = L$. Furthermore, since $\overline{n}$ denote the minimum required number of policyholders, we must have $\overline{n}_h, \overline{n}_l \in \mathbb{N}$.

A low-risk agent has a lower loss probability than a high-risk agent. Yet, if the loading is multiplicative, she also contributes less to the common reserves. In this case, a decrease in risk-bearing capital generated by a diminished proportion of high-risk policyholders θ cannot be balanced by an increased proportion of low-risk policyholders $(1-\theta)$, as it appears in the expression for collected premiums: $\theta n \pi_h + (1-\theta) n \pi_l$. Hence, in this case, there is no direct substitution between two risk types. Furthermore, insurance funds represented by premiums serve their purpose when losses can actually be covered. Since it requires a precise number and combination of policyholders to cover one loss, an additional policyholder does not necessarily improve the coverage capacity.

Consider a simple numerical illustration. Each agent faces a risk of losing one monetary unit: $L = 1$. A high-risk agent's loss probability is τ times higher than the one of a low-risk agent: $p_h = \tau p_l \,, \tau > 1\,.$ If premiums are proportional to the expected loss, a high-risk premium is also τ times higher: $\pi_l = 0.04$ and $\pi_h = 0.08$ $(\tau = 2)$. In a homogeneous pool, the amount of premiums required to cover exactly one loss is equal to $\frac{L}{\pi_k} = \frac{1}{p_k c}$. Since $p_h = \tau p_l$, the quantity of premiums required to cover exactly one loss in a high-risk pool is τ times lower. In other words, at least τ times less policyholders are required to cover one loss in a high-risk pool. The required minimum size would be either thirteen high-risk policyholders, or twenty-five low-risk policyholders: since high-risk agents contribute twice as much as low-risk agents, it takes at least twice as much low-risk policyholders to cover the same loss. If both types are allowed in the pool, then the minimum size required to absorb one loss is given by $\overline{n} = \left\lceil \frac{1-\overline{n}_h(0.08-0.04)}{0.04} \right\rceil$.

Suppose that we already have nine high-risk policyholders in the pool. Then, the minimum pool size is sixteen, and it would be necessary to add seven low-risk policyholders in order to accumulate enough funds to cover one potential loss. A high-risk policyholder could not be replaced by a low-risk one. The expected global loss in the pool decreases when a high-risk policyholder is replaced by a low-risk one, but it might also deteriorate the risk-bearing capacity by reducing the available funds. Next, if only six low-risk agents enter the pool, one accident would still be enough to make the pool go bankrupt. In other words, the risk-bearing capacity does not improve progressively with size, because the risk-bearing capital provided by policyholders improves the risk-bearing capacity only when those funds enable the coverage of one extra loss.

Chapter 3

Mutual or stock insurance: solidarity when insolvency matters

Summary of the chapter

This chapter analyzes the choice of the insurer, mutual or stock, for a heterogeneous population aware of the insurers' probability of insolvency. The stock insurer sets individualized premiums and manages his probability of insolvency by means of a premium loading, in contrast to the mutual insurer who sets an average premium and allows a possibility to adjust the premium level ex-post. We assume that information is symmetrical due to the data availability on individual characteristics and actions, and, as a consequence, that it is possible to perfectly differentiate risk types. Despite the idea that the individualization of insurance premiums is advantageous for the stock insurers and the low-risk agents, we show that under some conditions the mutual insurer is optimally preferred by the entire population of high-risk and low-risk agents. The existence of such an equilibrium depends on the relative weight of each group of risks in the population, and on the size of the risk loading. For a sufficiently small group of low-risk agents, an increase in the risk loading provides an incentive to pool their risk with the high-risk agents through mutual agreement.

Key words: information, insolvency, loading, mutualization, risk heterogeneity

JEL classification: D81, G22, L22

3.1 Introduction

In the economic literature, insurance contracts are generally defined as an exchange of an uncertain wealth for a certain one by means of premium payment. This assumption, however, excludes the possibility that the stock insurer will be unable to provide a full indemnity to each claimant. Nevertheless, it is well known that partial coverage can result from various real-world situations, such as insolvency, uncertain legal standards, or delays in claims reimbursement (Doherty and Schlesinger, 1990; K. Lee, 2012b).

Another common assumption in the modeling of insurance contracts is that the insurance premium is equal to the individual expected loss, plus administrative costs for running an insurance business. Yet, there exist other important sources of premium loading. For instance, the actuarial literature agrees on the role of the *risk* loading in managing the probability of insolvency.

In the perfect capital market it would be optimal for the stock insurer to raise a sufficient amount of external capital to completely avoid insolvency, and sell full insurance contracts at the price equal to the policyholder's expected loss (Rees et al., 1999; Laux and Muermann, 2010). However, insolvencies cannot be ruled out in the economic reality. Hence, we argue that the probability of insolvency is an important issue in the discussion related to the insurance companies and the insurance market functioning.

Besides the insurers' probability of insolvency, current information accessibility is a prominent issue that attracts the attention both of regulators and the general public. In particular, the use of information on the individual characteristics, which become observable through the analysis of new data, raises concerns about its potential impact on the conception of insurance contracts, classification, price discrimination, mutualization principle, and solidarity.

The majority of prominent findings in the economic literature are related to the information asymmetry problems and the need to make a distinction between different risk types without having direct knowledge on the individual risk level or the actions undertaken to mitigate the risk. For instance, given the information asymmetry and the adverse selection issue in particular, stemming from the insurer's inability to distinguish between high and low risks, the low-risk agents never benefit from pooling their risk with the high-risk agents. Consequently, the classic solution to the adverse selection problem results in the separation of two risk types through the menu of contracts, leaving low-risk agents only partially covered (Rothschild and Stiglitz, 1978).

Other findings suggest that in the context of information asymmetry, mutuals serve as a screening mechanism allowing to separate high and low risks between different types of insurers (B. Smith and Stutzer, 1990; Ligon and Thistle, 2005). However, given current technological advances and the resulting accessibility of information, the information *symmetry* becomes a relevant hypothesis.[1]

The classic economic theory predicts that the low-risk agents do not wish to pool their risk with the high-risk agents because of the associated cross-subsidization of insurance premiums. Assuming that insurers are informed about the policyholders' risk levels, the former should be able to distinguish between different risk types and offer low-risk agents full coverage for a lower premium according to their risk. Therefore, the individualization of insurance premiums is automatically presumed to be advantageous for the insurers and the low-risk agents.

In the present chapter, we aim to challenge this conception. We consider a stock insurer, who is assumed to charge individualized insurance premiums, and a mutual insurer, who is assumed to exert less price differentiation. Moreover, we include in our analysis the second dimension of interest, which is the probability of insolvency. Indeed, not only the premium policy can be different depending on the type of the insurer, but also the tools to manage the risk of insolvency and its consequences, as we will explain below.

Mutual insurers can issue a call for additional premium payments in case of insufficient financial reserves.[2] Stock insurers, on the other side, manage the probability of insolvency through loaded premiums. Hence, the stock insurance premium includes a risk loading that is used to create a buffer fund in order to cover the claims exceeding the expected global loss. The general functioning of the risk loading has been presented in Chapter 2, where we discussed how the risk loading affects the probability of insolvency. In addition to this relationship between the risk loading and the probability of insolvency, the present chapter introduces the effects of the loading on the policyholders, as well as the impact of insolvency through the recovery rates.

Given the differences in functioning between stock and mutual insurers, we model

[1]As it was mentioned in Chapter 1, another interesting assumption is a reversed information asymmetry that implies that the insurers are better informed on the individual risk level than the agents themselves (Villeneuve, 2000). An alternative but equally compelling assumption is a differential information asymmetry, which implies that different contracting parties have superior information regarding different elements affecting the risk (Seog, 2009).

[2]By design, mutual insurance can be based entirely on the ex-post defined premiums, such that the total loss is divided equally among the participants, thus constituting an efficient risk pooling of homogeneous risks (Borch, 1962; Fagart et al., 2002). Considering risk heterogeneity, Bourlès and Henriet (2012) show in a setting with two heterogeneous agents and one mutual that mutual risk-sharing agreement is an efficient insurance structure when the information is asymmetric, even if information asymmetry can still lead to a loss of efficiency.

a market with one mutual and one stock insurer to focus on those differences rather than the market dynamics. There exist arguments in favor of private stock insurers in the current context of data availability. We examine and challenge the idea that individualization will necessarily benefit the stock insurers and the low-risk policyholders. Moreover, given the long history of mutual insurance and the fact that mutuals are still widely present in the insurance market, we are interested in exploring the conditions making mutual insurance more attractive for a heterogeneous population of high-risk and low-risk agents. In particular, we focus on the conditions that make mutual insurance optimal for the low risks in presence of high-risk mutual participants.

When both insurers face a positive probability of insolvency and both are informed about the policyholders' risk types, the agents' choice between the mutual and the stock insurer is based on two criteria: insurance premium and expected indemnity. The stock insurance premium is individualized but includes a risk loading conditional on the size of the stock insurance portfolio, while the mutual insurance premium depends on the composition of the mutual pool. At the same time, agents are better covered in the mutual pool in case of insolvency, other things being equal because the risk of partial coverage resulting from the insurer's insolvency is spread equally across all the mutual participants. Alternatively, the stock insurance policyholders are affected by insolvency only when they claim a loss. We include those aspects in the agents' decision to choose the stock or the mutual insurer, thus contributing to the current debate on information accessibility, its potential use in the evaluation of risk profiles, and the assumed benefits for the low-risk agents and the insurers that offer individualized premiums.

We find that it is not always optimal for the low-risk policyholders to choose the stock insurance contract with individualized premium, contrary to the idea of the advantage provided by individualization. In particular, the low-risk agents are not necessarily better off choosing the stock insurance contract when the high-risk agents choose the mutual insurance contract. It can be optimal for the low-risk agents to participate in the mixed mutual pool with the high-risk agents by covering their risk together through the mutual insurer, depending on the weight of the low-risk group in the population and the size of the risk loading.

For instance, if the entire population is insured by the stock insurer, but individualized premiums make it more advantageous for the high-risk agents to choose the mutual insurer, the stock insurance portfolio will decrease in size. Given that the stock insurers must maintain a fixed level of the probability of insolvency for regulatory reasons, a decrease in the size of the portfolio will affect the premium level to compensate for the lack of reserves. Consequently, an increase in the premium level created by the high-risk agents switching from the stock insurer to the mutual insurer can provide incentives for the low-risk agents to join the mutual pool as well.

The rest of the chapter proceeds as follows. In Section 3.2, we provide a review of two global strands of literature related to our research question. In Section 3.3, we present the model illustrating the difference in functioning between a mutual and a stock insurer. In Section 3.4, we derive the conditions under which it is optimal for the low-risk agents to pool their risk with the high-risk agents by purchasing a mutual insurance contract. We pursue with a discussion in Section 3.5. The concluding remarks are provided in Section 3.6.

3.2 Related literature

The present chapter contributes to two strands of literature: the one on the impact of insurers' insolvency on the demand for coverage and the choice of contract type, and the other one on the differences between the mutual and the stock insurance and the coexistence of both organizational forms. First, we provide an overview of each subject in Sections 3.2.1 and 3.2.2. Then, in Section 3.2.3, we review some of the articles that are more closely related to our research question in that they combine both endogenous insolvency and stock and mutual insurers at the same time.

3.2.1 The impact of insurer's insolvency

There exists a large literature on the insurer's insolvency from the statistical point of view. Some contributions to this strand of literature were discussed in Chapter 2. Another approach to the subject of insurers' insolvency is to examine the ways in which insolvency affects policyholders.

When insurers are unable to meet their engagement of reimbursing claimants, the resulting coverage is partial and depends on the predefined recovery rate principle and the extent of insolvency. Various terms are used in the literature to describe the aforementioned situation, such as the probability of default, contract nonperformance, non-reliability of insurance coverage, partial performance, or uncertain indemnity. Some of those terms describe situations that extend to other issues (non-reliability of protection systems, such as unreliable fire alarm, or legal issues creating delays in claims treatment), but all of them include the possibility of insurer's insolvency and provide interesting insights on the ways of conceptualizing its impact on the policyholders.

One of the early instances of research that analyzes the demand for insurance in presence of default risk is provided by Tapiero et al. (1986). The authors examine theoretically the agents' decision to purchase full coverage from the mutual insurer by evaluating their willingness to pay for it given a positive probability of insolvency. In particular, they compute the actuarial loading factors given the probability of default in a homogeneous pool, its size and the policyholders' risk aversion.[3] As the authors pinpoint in the conclusion, the relationship between the default risk and actuarial loading factors is neglected because of the assumption of large portfolios. Yet, when the number of insureds is not too large, the default risk might become important.

Interestingly, Tapiero et al. (1986) also make a distinction between two following notions: the probability of insolvency, which is the probability that the insurer will not be able to cover all the losses that occurred at the end of the period, and the *perceived* probability of insolvency, which is the probability that a given policyholder will be affected by the insolvency.[4] In Section 3.3, we will return to the concept of loaded premiums and to the idea of the perceived probability of insolvency defined as the probability of being affected by the latter.

The research on the impact of the default risk follows with the findings that link the insurance demand to the risk aversion in the context of partial coverage resulting from the insurer's insolvency. The relationship between Arrow-Pratt risk aversion and insurance demand given a possibility of total default is modeled and studied by Schlesinger and Schulenburg (1987). The authors show that more risk-averse agents do not necessarily choose a higher level of coverage when insolvency is possible, explaining this observation by the fact that the possibility of insolvency exacerbates the downside risk. Indeed, in the case of an insurer's insolvency, the worst state of the world, which is the one where the loss is realized, deteriorates even further with a purchase of insurance coverage given a positive probability of suffering a loss and not being indemnified.[5]

[3]The authors highlight the inter-dependency between premiums and insolvency that is reflected by the optimal premium rates. The premium rate is adjusted through the premium loading which depends on the risk of insolvency, while the risk of insolvency is determined by the premium rate. We have also explained this link between the risk loading and the probability of insolvency in the previous chapter.

[4]In Tapiero et al. (1986), the notion of perceived probability illustrates the fact that policyholders are not systematically affected by their insurer's insolvency. Putting aside the need to find a new insurer if the current insurer becomes insolvent, only the policyholders that file a claim are affected by their insurer's insolvency through the incomplete coverage. The possibility that each policyholder has a different perception of the probability of insolvency, i.e. has beliefs regarding its level which are different from the objective probability and from the beliefs of the insurer himself, is examined by Cummins and Mahul (2003).

[5]K. Lee (2012b) confirms the observation that the downside risk is important in the case of a

Doherty and Schlesinger (1990) continue the work started by Schlesinger and Schulenburg (1987) by extending the analysis on the relationship between the risk aversion and the optimal demand for insurance in the context of what the authors call a contract nonperformance.[6] They describe the latter as a source of the risk of losing the premium in addition to the loss, thus excluding from the analysis the possibility of partial default, similar to Schlesinger and Schulenburg (1987).[7] In addition to the previous results concerning risk aversion, the authors show that an increase in the probability of insolvency does not necessarily decreases the demand for coverage. In particular, the demand for coverage is shown to be a non-monotonic function of the probability of default which depends both on the risk aversion and the risk loading. Later, Briys and Schlesinger (1990) extend those findings by allowing for a continuous distribution of full and partial default and confirm previously documented departure from classic results concerning risk aversion and optimal demand for coverage.

The literature mentioned above focuses on a homogeneous population of policyholders. The research on the effect of insolvency given a heterogeneous population of policyholders can be found in the literature on adverse selection. For instance, Agarwal and Ligon (1998) model the impact of the risk of insolvency on the adverse selection equilibrium, building on the framework provided by Wilson (1977). They consider the probability of total default as an uninsurable risk emerging from the correlation between the individual risks. Given this context, the authors confirm the ambiguity of results, stated by previously cited authors, and derive a possibility of surprising implications. Namely, if the initial situation implies a separating equilibrium and the introduction of the default risk induces the shift to the pooling equilibrium, the authors show that the high risks might be better off. The underlying reason is that the default risk decreases the relative pricing difference between two risk classes, and in particular it decreases the cost of pooling for the low-risk agents.

In addition to the policyholders' heterogeneity, Mimra and Wambach (2017) model an extension to the framework build by Rothschild and Stiglitz (1978) by introducing the endogenous insolvency through the insurers' choice of capital level.

possibility of partial coverage because the uncertain indemnity creates two effects. It creates an additional risk, which makes less coverage optimal, but it also creates an additional precautionary motive for prudent agents, so more coverage can be optimal depending on the level of prudence.

[6]The authors give multiple interpretations of the notion of contract nonperformance, such as insolvency, uncertain legal standards or delays in claims reimbursement.

[7]In their framework, partial default is not possible. There are only three states of nature: the one where the agent does not suffer a loss, the other one where the agent does suffer a loss but is fully covered, and the last one where the loss cannot be indemnified.

They show that under the assumption of the possibility of insolvency, the policyholders' expected utility depends on the other policyholders' risk profiles. This inter-dependency creates an externality that guarantees a stable separating equilibrium with the fully insured high-risk agents and partially insured low-risk agents subsidizing high-risk agents through unfair premiums. The stability is ensured by the fact that high-risk agents will follow low-risk agents deviating to another insurer since their deviation will deteriorate the probability of the insurer's insolvency for the remaining high-risk agents. The authors also show that collecting more capital is not optimal for an insurer as it might incentivize other insurers to attract low-risk agents by offering lower prices.

Regarding the endogenous level of capital, Rees et al. (1999) show that in a competitive setting, when consumers correctly perceive the endogenous probability of an insurer's insolvency, it is always optimal for the insurer to collect enough capital to rule out the possibility of insolvency. Yet, the existence of solvency regulation suggests that insurers do not necessarily provide certain solvency, and it might even not be possible. For example, restrictions on the composition of the insurer's asset portfolios, correlation between individual risks or the state of financial markets might all limit the insurer's capacity to rule out insolvency entirely. Moreover, Hamwi et al. (2004) show that solvency regulation requiring a low level of probability of insolvency is not necessarily beneficial for policyholders, since it usually requires higher premiums because of higher regulatory costs. In our model developed in Section 3.3, the endogenous risk of insurer's insolvency stems from the limited financial reserves and is reflected through the presence of the risk loading.

3.2.2 Stock and mutual insurance considered together

The findings presented above focus on one type of insurer. We will now present some literature that considers both stock and mutual insurers. It should be noted first that there exists in fact a large strand of literature on the coexistence between mutual and stock insurers from the point of view of agency theory. As argued by Mayers and C. Smith (1988), one reason for the coexistence between stock and mutual insurance forms is the differences in their ownership structure which allow preventing different types of agency conflicts. For instance, the fact that a mutual insurance firm belongs to its policyholders allows preventing conflicts between shareholders and owners of the firm. At the same time, the advantage of the stock insurance organizational structure lies in providing higher incentives to control the firm managers. Since we are not focusing on the agency conflicts in the present thesis, we will provide an overview of the literature on the alternative reasons for coexistence between both organizational forms.

Considering the heterogeneity of insured risks, B. Smith and Stutzer (1990) argue that stock and mutual insurance firms coexist because they allow solving the adverse selection problem. In particular, the authors show that low-risk agents can signal their type by choosing a mutual insurance contract and thus accepting to share the aggregate risk through the mutual pool, while high-risk agents will remain covered by the stock insurer. In a similar vein, Ligon and Thistle (2005) explain the existence of small mutual firms by suggesting that the size of a mutual firm can be a tool used to prevent high-risk agents from following low-risk agents forming a mutual pool. Hence, if the mutual pool satisfies a self-selection constraint related to its size, low-risk agents choose to share their risk through the mutual pool, while high-risk agents are optimally covered by the stock insurer.

Alternatively, Picard (2014) argues that in the adverse selection context, participating policies associated with the mutual insurance act as an implicit threat rather than a screening mechanism. He shows that such contracts prevent other insurers from cream-skimming low risks, since attracting low risks will necessarily attract high risks as well, due to the high risks' deteriorated situation created by the departure of low risks to another insurer.[8]

Another possible explanation linked to the information asymmetry is provided by B. Smith and Stutzer (1995). Given the nature of mutual agreements, the authors suggest that mutual insurance provides a way of reducing a moral hazard. The authors show that the participating nature of mutual insurance might create incentives for the policyholders to engage in preventive efforts by making them bear a part of the total risk. At the same time, Ligon and Thistle (2008) analyze the comparative advantage of mutual and stock insurers in reducing the moral hazard and show that the presence of an uninsurable background risk inherent in mutual insurance should make stock insurance preferable in the competitive market with moral hazard.

An interesting point noted by Picard (2014) is that participating contracts are not tied to the mutual insurance form. Friesen (2007) also drives attention to the fact that participating contracts associated with mutual insurance can be issued by stock insurers as well, but are rarely used by the latter. He suggests that stockholders cannot set appropriate premiums with a fair and acceptable expected return on their investment when contacts are fully participating.[9] While partially participating

[8] As it was mentioned previously, this result has been later confirmed by Mimra and Wambach (2017) in the context of the possibility of insurers' insolvency.

[9] Fully participating contracts require that stockholders retain a part of the risk of default, yet they simultaneously decrease the profits generated by the contracts.

contracts can be profitable for stockholders, they are generally less desirable for the policyholders than fully participating contracts from a mutual firm.[10]

As we mentioned before, most of the findings are either related to the homogeneous population of policyholders, or to one type of insurer, or to the exogenous probability of insolvency. In the present chapter, we are interested in the symmetric information case where both the mutual and the stock insurers can learn each agent's risk type before contracting, while the agents are aware of the probability of insolvency. In the next subsection, we discuss some literature that is more closely related to our setting.

3.2.3 Endogenous insolvency with both stock and mutual insurers

While discussing the insolvency issues, it is important to consider that the probability of insolvency is endogenous and it is indeed linked to the capital level. Consequently, it is useful to examine the difference between stock and mutual insurance in terms of financial reserves and premiums.

Laux and Muermann (2010) examine both insurance forms in presence of frictional cost of capital, transaction costs, and governance problems. They show that stock insurance policyholders have an incentive to free-ride on the capital provided by others, which is not the case for the mutual form. Considering the differences in stock and mutual insurance premiums structure from the theoretical perspective, Braun et al. (2015) use the empirical data to verify the presence of those differences in practice. Their study shows that both types of insurers charge the same premium level, which implies from the theoretical point of view that mutual insurers hold substantially less capital. Yet, it is not a plausible assumption given solvency requirements prohibiting such a decrease in capital level. Thus, the authors suggest that stock insurance premiums are overpriced, probably due to the lack of competition or policyholders' unawareness regarding the difference in functioning between mutual and stock insurance.

Considering the interactions between stock and mutual insurers given endogenous insolvency, Bourlès (2009) examines the cases when a stock insurer with endogenous capital level can enter the market with one mutual insurer. He shows that it is more likely that a stock insurer profitably enters the market when the size of

[10]When participation fraction is high, they are not desirable because the premium charged by stockholders to reduce the probability of default is high in this case. And when participation fraction is low, partially participating contracts can be desirable for highly risk-averse policyholders, but are not widespread because of regulatory constraints prohibiting partially participating contracts.

the insured population and the risk level are high, and the capital cost is low. In this case, the stock insurer will insure the entire market by choosing a high level of capital. Fagart et al. (2002) examine the coexistence of both types of insurers in a competitive setting with endogenous capital level and show that multiple configurations are possible at the equilibrium. In particular, both mutual and stock insurers can coexist if the stock insurer is limited in size because of the fixed capital stock. However, the authors consider a homogeneous population, while we are interested in a heterogeneous population. Moreover, we model the market with one mutual and one stock insurer to focus on their structural difference.

The framework that is most closely related to the issue we treat is provided by Charpentier and Le Maux (2014). The authors examine the attractiveness of the government-provided insurance program, similar in its functioning to mutual insurance, compared to the limited-liability insurer in the context of natural catastrophe insurance. They show that government-provided insurance is more attractive for a homogeneous population since negative externalities of insolvency are better spread through the mutual-like form.[11] In particular, the willingness to pay for such coverage is higher, thus leading to a lower probability of insolvency. Nevertheless, in a heterogeneous context where different policyholders belong to different geographical regions with different correlation levels, government-provided insurance might be less attractive for the safer regions. The difference between the authors' work and our framework stems from the fact that we consider the heterogeneity in the probability of loss rather than the correlation between risks.

In the following section, we will present our model with two types of insurers, one mutual and one stock insurer. We will introduce the endogenous probability of insolvency and present the differences in functioning between two insurers, in terms of premiums and the ways of managing the insolvency. We will follow with additional assumptions needed in order to examine the optimal choice of the insurer's type for a heterogeneous population of risks.

[11] Doherty and Dionne (1993) also pinpoint the fact that mutuals are especially widespread in insurance sectors where losses are correlated, meaning that some part of risk cannot be diversified and eliminated by pooling. They show that mutual firms provide an efficient Pareto-optimal risk-sharing arrangement by spreading the non-diversifiable risk between the mutual participants.

3.3 The model with two types of insurers and endogenous insolvency

Consider a population of K independent and risk averse agents with the same preferences represented by the von Neumann-Morgenstern utility function U defined over final wealth, $U' > 0\,, U'' < 0\,.$ Each agent is endowed with a non-random initial wealth w and faces a risk of losing a monetary amount $L\,, L < w$. The individual loss probability is noted $p_i\,, i = 1, ..., K\,.$ Thus, without insurance, the final wealth of an agent i is a lottery $\widetilde{w}_i = (w, 1 - p_i\,; w - L, p_i)\,.$

Insurance is considered to be mandatory.[12] It is provided by one mutual insurer and one stock insurer. An agent i chooses either to join the mutual pool managed by the mutual insurer or to purchase a contract from the stock insurer. We assume that all the capital is provided by policyholders through the premiums, and there is no reinsurance in our model.[13] An insurer collects premiums at the beginning of the period and pays claims at the end.

The total amount of claims may exceed the amount of collected premiums, thus both insurers face the risk of insolvency represented by a simple one-period model of insurer's risk of ruin. Information on individual loss probability and insurer's insolvency probability is complete and symmetrical: both the individual and the insurer she chooses to contract with have the same information about the agent's individual loss probability and the insurer's probability of insolvency.[14]

The insolvency occurs when the insurer does not have enough funds to provide full coverage to all the claimants. The probability of insolvency, therefore, measures the probability that the total amount of loss will be larger than the total premiums amount. Let the random variable $\tilde{N}$ denote the number of claimants in the mutual pool, or equally in the stock insurance portfolio, with $N = 0, 1, ..., n$ denoting the realization of $\tilde{N}$. Then, the stochastic amount of total loss is given by $\tilde{N}L$. Let π_i denote the individual premium of an agent i. Its exact structure will depend on the

[12] First, the insurance coverage is often mandatory for some specific branches. For instance, in France, automobile insurance, health insurance and property and casualty insurance are mandatory. Second, if we consider the decision to buy insurance, we will have to consider two different decisions: to buy the insurance coverage or not, and then from which insurer. This would make the problem much more complex. Since the decision to purchase insurance or not has been well studied in the literature, we consider that insurance is mandatory in order to focus on the choice between the stock and the mutual insurers.

[13] We do not consider the possibility of reinsurance given that the mutual and the stock insurers have the same access to the reinsurance market. Consequently, the introduction of the reinsurance in our model should have no impact on the results.

[14] The assumption regarding the availability of the information on the agents' loss probability is explained by our focus on the current data accessibility.

insurer's type and will be presented in the dedicated subsections. Finally, if there are n policyholders in the mutual pool, or equally in the stock insurer's portfolio, then the insurer's probability of insolvency denoted by q is given by

$$q = \Pr\left(\tilde{N}L > \sum_{i=1}^{n} \pi_i\right). \tag{3.1}$$

We further denote by $\tilde{X}$ the random share of claimants in the mutual pool or in the stock insurance portfolio:

$$\tilde{X} = \frac{\tilde{N}}{n}. \tag{3.2}$$

The random variable $\tilde{X}$ is defined over the interval $[0, 1]$, with the density function $f(x)$ and the distribution function $F(x)$. We also denote by $\overline{x}$ the largest fully insurable share of claimants, which is the maximum percentage of policyholders that can potentially receive a total coverage. The insurer can cover up to $\frac{\sum_{i=1}^{n} \pi_i}{L}$ losses, consequently the insurer can reimburse $\left(\frac{\sum_{i=1}^{n} \pi_i}{nL} \times 100\right)\%$ of the total number of policyholders at maximum:

$$\overline{x} = \frac{\sum_{i=1}^{n} \pi_i}{nL}. \tag{3.3}$$

Then, we can rewrite Eq. (3.1) as

$$\begin{aligned} q &= \Pr\left(\tilde{X} > \frac{\sum_{i=1}^{n} \pi_i}{nL}\right) \\ &= \Pr\left(\tilde{X} > \overline{x}\right) \\ &= 1 - F(\overline{x}). \end{aligned} \tag{3.4}$$

Note that there exist multiple possible states of insolvency associated with a share of claimants x such that the insurer cannot provide a full coverage to all the claimants; i.e. with $x > \overline{x}$.

The impact of the insurer's insolvency on a given policyholder depends on the insurer's type. Given the difference between the mutual and the stock insurers, the impact of insolvency can be different both in terms of the affected group and severity. In particular, mutual and stock insurers have different pricing strategies, which result in different premium structures, and they also use different mechanisms to manage the possibility of insolvency. Thus, a policyholder's final wealth is a lottery conditional on the type of insurer she chooses to contract with. The different impact of two types of insurers on the policyholder's expected utility are presented in the rest of this section.

3.3.1 Stock insurer: individualized premiums and the risk loading

The stock insurer sets individualized premiums based on the policyholder's individual risk level. The premium is calculated according to the policyholder's expected loss. Moreover, the stock insurer can manage his probability of insolvency ex-ante by charging the premium with a risk loading.[15] The latter enables the accumulation of financial reserves, which constitute a buffer fund providing insurer's risk-bearing capacity.

We denote by c the risk loading and we consider that the risk loading is additive. Thus, it is added to the pure premium which is based on the policyholder's expected loss $p_i L$. Then, the stock insurance premium for a policyholder i writes

$$\pi_i^S = p_i L + c\,. \tag{3.5}$$

The size of the risk loading is chosen depending on the desired level of the probability of insolvency, denoted by $\overline{q}$, and on the size of the stock insurance portfolio. Hence, for the chosen level of the probability of insolvency $\overline{q}$, the risk loading $c\,(\overline{q}, n)$ is such that

$$\Pr\left(\tilde{X} > \frac{\sum_{i=1}^{n}\Big(p_i L + c\,(\overline{q}, n)\Big)}{nL}\right) = \overline{q}\,, \tag{3.6}$$

If the amount of collected premiums is lower than the amount of the aggregate claims, the stock insurer reimburses the claimants to the extent of the available funds and goes bankrupt. The stock insurer cannot call for an additional contribution from the policyholders, contrary to the mutual insurer, as we explain it below. That means that three states of nature are possible from the stock insurance policyholder's point of view.

With the probability $1 - p_i$, the policyholder i does not suffer a loss, and in this case the stock insurer's solvency state does not affect the policyholder's utility: it is irrelevant whether the insurer is solvent or not. Otherwise, there is a probability p_i that the policyholder i does suffer a loss. In this case, depending on the insurer's

[15] The risk loading was discussed in more detailed manner in Chapter 2. It is different from the expense loading, which is used to cover administrative costs from running an insurance business.

situation (solvent or not), the policyholder will receive a full or a partial indemnity.

If the stock insurer is solvent, the indemnity is full, and the resulting wealth is the same as when no loss occurs. If the stock insurer is insolvent, the indemnity is less than full. The resulting partial indemnity is determined by the global amount of claims in the portfolio. In other words, the stock insurer distributes the available funds (the sum of the premiums) to the claimants.

As it has been mentioned before, there exist multiple possible states of insolvency, depending on the random share of claimants $\tilde{X}$ in the portfolio. In particular, for an agent i the stock insurance indemnity $I(.)$ depends on the realization of $\tilde{X}$. For a given realized share of claimants x, the stock insurer is solvent and the indemnity is full if the maximum available amount per claimant is at least as high as the loss L, which is the case if the share of claimants is smaller than the largest insurable share of claimants as defined by Eq. (3.3):

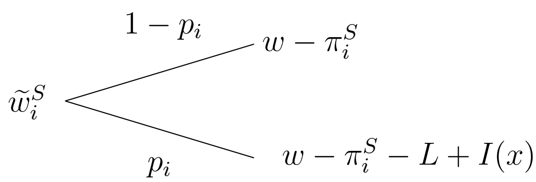
$$I(x) = L \quad \text{if} \quad x \leq \overline{x}\,. \tag{3.7}$$

Otherwise, the insurer is insolvent and distributes the available funds between all claimants so that each claimant receives a partial coverage:

$$I(x) = \frac{\sum_{i=1}^{n} \pi_i^S}{nx} < L \quad \text{if} \quad x > \overline{x}\,. \tag{3.8}$$

Figure 3.1 illustrates the resulting lottery on final wealth for the stock insurance policyholder i.

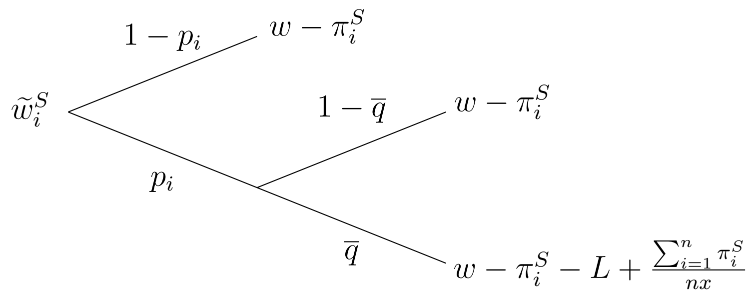
Figure 3.1: Stock insurance policyholder's final wealth (one-stage lottery)



Overall, if the agent i chooses the stock insurance contract, her final wealth $\widetilde{w}_i^S$ will depend on her chances to become claimant, p_i, and on the stock insurer's probability of insolvency $\overline{q}$ if she files a claim. Thus, the final wealth for the stock insurance policyholder i can also be represented as a multi-stage lottery illustrating three states of nature described previously.

Figure 3.2 provides such an illustration. It highlights the fact that for the stock insurance policyholder i, the probability to be affected by insolvency $\overline{q}p_i$ is indeed more relevant than the actual probability of insolvency $\overline{q}$, since she is affected by her insurer's insolvency only when she files a claim herself. Note that in Figure 3.2, the indemnity represented by $\frac{\sum_{i=1}^{n} \pi_i^S}{nx}$ is such that $x > \overline{x}$, given that $\overline{q}$ is the probability that x will be higher than $\overline{x}$, as it is introduced by Eq. (3.6).

Figure 3.2: Stock insurance policyholder's final wealth (multi-stage lottery)



Now let us write the expected utility of an agent insured by a stock insurer. The expected utility of a stock insurance policyholder can be written as

$$\mathbb{E}U(\tilde{w}_i^S) = (1 - p_i)\, U(w - \pi_i^S) + p_i \mathbb{E}\Big(U\left(w - \pi_i^S - L + I(\tilde{X})\right) \mid \tilde{X} > 0\Big)\,, \tag{3.9}$$

following the illustration provided by Figure 3.1.

3.3.2 Mutual insurer: average premiums and ex post adjustment

Historically, mutual participants are the members of the mutual agreement who decide to pool their risk together and apply the solidarity principle. Thus, the mutual belongs to its policyholders, and less price differentiation is often observed. The mutual premium can provide various degrees of differentiation and it is not necessarily individualized, compared to the stock insurance premium.

The mutual premium can vary from a perfectly individualized premium ($\pi_i^M = p_i L$) to an average premium based on the aggregate risk estimation, $\pi_i^M = \pi^M = \overline{p}L$, with $\overline{p} = \frac{\sum_{i=1}^{n} p_i}{n}$ in the mutual pool of size n. We assume that the mutual insurer charges an average premium:

$$\pi^M = \overline{p}L\,. \tag{3.10}$$

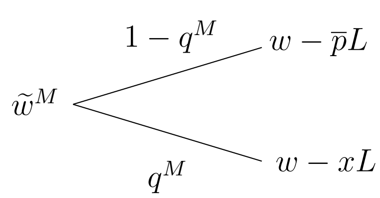
The mutual insurer has a possibility to adjust the premium level ex-post at the end of the period, if the collected premiums are not sufficient to cover the total amount of loss. Consequently, he does not use the risk loading, as opposed to the stock insurer. The mechanism of ex-post premium adjustment allows the mutual insurer to exclude the occurrence of default. We denote by q^M the mutual insurer's probability of insolvency. Following Eq. (3.1), it writes as

$$\begin{aligned} q^M &= \Pr\left(\tilde{N}L > n\overline{p}L\right) \\ &= \Pr\left(\tilde{X} > \overline{p}\right) . \end{aligned} \tag{3.11}$$

In contrast to the stock insurer's customers, the mutual participants are affected by their insurer's insolvency all in the same way, regardless the realization of their individual risk. The ex-post adjustment is applied to the entire mutual pool if the adjustment is needed. Consequently, if an agent i chooses the mutual insurance contract, her final wealth $\widetilde{w}_i^M = \widetilde{w}^M$ is unconditional on her loss and depends only on the mutual insurer's probability of insolvency q^M.

If the mutual insurer is solvent, the indemnity is full, the same way it is for the stock insurer (Eq. (3.7)). Whenever the mutual insurer is insolvent, each mutual participant will have to retain an equal share $\frac{1}{n}$ of the total financial shortage. The financial shortage being equal to $NL - n\overline{p}L$, as it appears from Eq. (3.11), each mutual participant will retain an amount equal to $xL - \overline{p}L$. Hence, in case of insolvency, each claimant receives a partial indemnity $L-(xL-\overline{p}L)$, and each other policyholder contributes an additional amount $xL - \overline{p}L$ on top of the premium, leaving each mutual participant with the final wealth equal to $w - xL$. The ex-post adjusted payment in case of insolvency, xL, is equal to the average loss per head in the pool. Figure 3.3 illustrates the described lottery on final wealth in the mutual insurance case.

Figure 3.3: Mutual insurance policyholder's final wealth (one-stage lottery)



Thus, both claimants and non claimants have the same final wealth in case of the mutual insurer's solvency and insolvency, revealing the solidarity principle implicit in the mutual risk sharing. Consequently, instead of defining the final wealth through the indemnity $I(x)$, let $A(x)$ denote the ex-post adjustment amount applied to each mutual participant. The ex-post adjustment is equal to zero if the mutual insurer is solvent:

$$A\,(x) = 0 \quad \text{if} \quad x \leq \overline{x}\,. \tag{3.12}$$

If the mutual insurer is insolvent, the financial shortage is divided among all the participants, and the adjustment amount is equal to:

$$A\,(x) = xL - \overline{p}L \quad \text{if} \quad x > \overline{x}\,. \tag{3.13}$$

Then, the lottery on final wealth for the mutual participant can also be illustrated by Figure 3.4.

Figure 3.4: Mutual insurance policyholder's final wealth

$$\tilde{w}^M \; \overset{1}{\rule{3cm}{0.4pt}} \; w - \overline{p}L - A(x)$$

Hence, we can also write the mutual insurance policyholder's expected utility of final wealth $\tilde{w}^M$ in the following way:

$$\mathbb{E}U(\tilde{w}^M) = \int_0^1 U\Big(w - \overline{p}L - A(x)\Big) f(x)dx\,. \tag{3.14}$$

Compared to the expected utility of a stock insurance policyholder (Eq. (3.9)), Eq. (3.14) confirms that in the mutual insurance case, all the participants are affected in the same manner, regardless the individual loss realization.

In the next section, we consider the choice of the insurer's type, first for a homogeneous population of risks. We then proceed with the introduction of a heterogeneous population that comprises low and high risks. We examine the conditions making the mutual insurer advantageous compared to the private stock insurer.

3.4 The choice of the insurer's type

First, we provide the following result on the optimal choice of the insurer's type for a homogeneous population of agents.

Proposition 3.1. *When the population is homogeneous and the stock insurer does not introduce a risk loading ($c = 0$), at equilibrium, the entire population is covered by the mutual insurer.*

Proof. See Appendix B.1. □

When the population is homogeneous, the agents have the same loss probability ($p_i = p$). If the stock insurance risk loading is equal to zero ($c = 0$), the mutual and the stock insurance premiums are equal ($\pi^M = \pi^S = pL$), and so is the maximum insurable loss ($\overline{x} = p$). In this setting, we obtain the same result as the one provided by Charpentier and Le Maux (2014): the lottery on final wealth resulting from the purchase of the stock insurance contract is a mean-preserving spread of the lottery resulting from the purchase of the mutual insurance contract. Consequently, the mutual insurance contract is preferred by all risk-averse expected utility maximizers. Other things being equal, agents benefit from the mutual principle of sharing the total loss among all the participants.

Now, let us represent a heterogeneous population as n independent individual risks with two risk types: low risks (l) and high risks (h). There are n_h high-risk agents and n_l low-risk agents, with $n_h + n_l = n$. We denote by θ the proportion of high risks in the population: $n_h = \theta n$ and $n_l = (1-\theta)n$. We also denote by p_k each agent's individual loss probability, with $k = h, l$, $0 < p_l < p_h < 1$.

We assume that the decision to purchase a stock or a mutual insurance contract is simultaneous, and it is jointly made by each homogeneous group of agents.[16] Thus, the choice of the insurer's type can be imagined as a two players game where each player is the entire low-risk or high-risk group. The players, represented by two risk groups, decide to purchase one of two available contracts. The set of possible actions for each player is $\{M, S\}$, where M stands for the purchase of the mutual insurance contract, and S for the stock insurance contract.

In this context, the result of Proposition 3.1 applies to the situations in which the proportion θ of the high risks in the population is equal to zero or one. It helps us to derive the result for a heterogeneous population.

Corollary 3.1. *When the population is heterogeneous and the stock insurer does not introduce a risk loading ($c = 0$), there exist critical values $\hat{\theta}$ and $\hat{\hat{\theta}}$ of the proportion of high risks θ such that:*

i) when $\theta < \hat{\theta}$, the low-risk agents prefer the mutual insurer to the stock;

[16] Recall that the expected indemnity is conditional on the global amount of claims and is therefore determined by the size and the composition of the mutual pool or the stock insurance portfolio. Consequently, without the assumption of a simultaneous decision jointly made by each risk group, each agent's individual decision to choose the stock or the mutual insurer would depend not only on the differences between the two, but also on the other agents' choice. The choice problem would therefore be different for each additional policyholder, making it much more complex to analyze.

ii) when $\theta > \hat{\hat{\theta}}$, the high-risk agents prefer the mutual insurer to the stock.

Proof. See Appendix B.2. □

Indeed, since the utility function $U(.)$ is continuous and so is the expected utility function $\mathbb{E}U(.)$, there exists a proportion of the high-risk agents sufficiently small (or sufficiently large) so that the mutual insurer is still preferred by the low-risk group (high-risk group) when the risk loading is equal to zero.

In terms of the two players game, Corollary 3.1 implies that the strategy S (choosing the stock insurer) is strictly dominated by the strategy M (choosing the mutual insurer) for the group of type k agents when the group is large enough and the risk loading is equal to zero.

For instance, let us assume that everybody is initially insured through the stock insurer. Then, if the proportion of the low-risk agents is sufficiently high ($\theta < \hat{\theta}$), it is optimal for them to choose the mutual insurer alone rather than the stock insurer with the high-risk agents.

If this is the case, and it is optimal for the low-risk agents to choose the mutual insurer, it is also true for the high-risk agents. Indeed, if the low-risk agents choose the mutual insurer, the high-risk agents benefit from joining them, since this mutual pool provides a lower premium to the high-risk agents and decreases the expected rest on charge in case of insolvency. Thus, if the proportion of the high-risk agents is lower than the critical value $\hat{\theta}$, and the risk loading is equal to zero, both the high-risk and the low-risk agents can optimally choose the mutual insurer.

Nevertheless, it is not necessarily optimal for the low-risk agents to join the high-risk agents in the mutual pool. For instance, if the proportion of the low-risk agents is sufficiently small ($\theta > \hat{\hat{\theta}}$), and the risk loading is equal to zero, the high-risk agents prefer the mutual insurer to the stock. In this case, for the low-risk agents, the choice of the mutual insurer implies that the global risk distribution in the mutual pool will be close to X_h. In other words, the average risk level in the population tends to the high risk level, $\overline{p} \to p_h$.

Let us now consider an increase in the size of the risk loading. It can further be shown that the risk loading has a positive impact on the policyholder's expected utility only if the probability of insolvency is lower than some critical value $\hat{x}$.

Proposition 3.2. *An increase in the risk loading has a positive (negative) impact on the stock insurance policyholder's expected utility if $\overline{x} < \hat{x}$ ($\overline{x} > \hat{x}$).*

Proof. See Appendix B.3. □

Proposition 3.2 implies that an increase in the risk loading c has a positive or a negative impact on the policyholder's expected utility, depending on the stock insurer's initial probability of insolvency. An increase in the risk loading generates an accumulation of reserves forming the buffer fund, thus increasing the maximum insurable share of claimants $\overline{x}$ and consequently decreasing the probability of insolvency. At the same time, an increase in the risk loading has a negative impact on the expected utility because of the premium increase. If the probability of insolvency is high ($\overline{x} < \hat{x}$), the positive impact associated with the decrease in the probability of insolvency outweighs the negative impact of the premium increase. The overall impact is negative otherwise. Hence, we can make a following proposition, given the results provided by Corollary 3.1 and Proposition 3.2.

Proposition 3.3. *The mutual insurance is preferred by the entire heterogeneous population of high-risk and low-risk agents if $\theta > \hat{\hat{\theta}}$ and $c > \hat{c}$.*

It follows from Corollary 3.1 and Proposition 3.2 that an increase in the stock insurance risk loading can provide an incentive for the low-risk agents to join the high-risk agents in the mutual pool. The stock insurer is not necessarily more attractive than the mutual insurer for the low-risk agents. Consider that everybody is initially insured through the stock insurer, and that it is optimal for the high-risk agents to switch to the mutual insurer ($\theta > \hat{\hat{\theta}}$). If the high-risk agents switch to the mutual insurer, their departure from the stock insurance portfolio will generate an increase in the risk loading for the remaining low-risk agents, given that the stock insurer has to comply to a predefined level of the probability of insolvency. Then, if the resulting size of the risk loading is high ($c > \hat{c}$), the relative benefit of the decreasing global risk level is outweighed by the increase in the premium level, to the point that the mutual insurance provides a higher expected utility to the low-risk agents as well.

3.5 Discussion

Insolvency represents a subject of interest especially since the reform of the European Union insurance regulation and the Solvency II Directive, which came into effect in 2016. In particular, it introduces the *Solvency Capital Requirement* (SCR). The latter is defined as the amount of capital to be held by an insurer to meet his obligations to policyholders and beneficiaries over the following year with a probability of 99.5%. According to the report made by *European Insurance and Occupational Pensions Authority* (EIOPA), 180 insurers were affected by insolvency from 1999 to 2016. The primary cause being cited is the technical provisions evaluation risk, while the most commonly reported early identification signal is the deteriorating capital strength and (or) low solvency margin (EIOPA, 2018).

Mutual and stock insurers have different approaches to risk management, both in terms of the probability of insolvency and of the use of information on risk types. One most fundamental difference between mutual and stock insurance is the reciprocity of mutual risk-sharing. Mutual participants collectively retain the residual risk, spreading the financial shortage among all the participants.

The participating policies, which are essentially mutual insurance contracts, receive less attention in the literature than the classic stock insurance contracts. Nevertheless, the risk of insolvency generates externalities among agents, which are better spread in the mutual insurance case. Doherty and Dionne (1993) argue that the mutualization principle provides more general efficiency, while the risk transfer is efficient when the law of large numbers applies. The application of the law of large numbers relies on the assumption of the large stock insurance portfolios, yet this condition is not always met. If the portfolio size is not sufficiently large, the risk loading is used to maintain the probability of insolvency on a predefined level.

In our framework, the capital is normalized to zero both for the stock and the mutual insurer. If we assume that both insurers have the equivalent positive amount of capital at the beginning of the period, it would imply that the maximum insurable loss is higher than otherwise for both insurers. Consequently, if the amount of capital is high enough so that the probability of insolvency is sufficiently low even without the risk loading ($\overline{x} > \hat{x}$ when $c = 0$), it follows from Corollary 3.1 that any increase in the risk loading will generate a negative impact on the stock insurance policyholders' expected utility. As a result, mutual insurance will be always preferred by a homogeneous population. If we assume that only the stock insurer collects capital through the external stockholders prior to selling policies, it will decrease the stock insurer's probability of insolvency. In this case, the condition for the mutual insurer to be preferred will be harder to be met.[17]

Furthermore, we assume that the mutual insurer exerts only negative premium adjustments. However, mutuals belong to their policyholders. Consequently, the latter can equally receive ex-post discounts in case of a financial surplus, if such a possibility is specified by the mutual policy. In this case, there is a possibility of both negative and positive ex-post premium adjustments. Our results can be extended to such contracts, which are in fact fully participating policies. The assumption of

[17]It would not make the risk loading irrelevant, except if there is a possibility to collect an infinite amount of capital. Even then, a loading called the risk premium would be charged to compensate the investors, as argued by Doherty and Dionne (1993).

positive adjustment would relax the condition on the critical values by making the mutual insurer more attractive.[18]

The existence of the pooling equilibrium with both high-risk and low-risk agents choosing the mutual insurer depends on the relative size of each group in the population. Naturally, it also depends on the distance between the two risk levels. The closer the two groups are in terms of the individual probability of loss, the higher is the range of values of θ and c allowing for the existence of the pooling equilibrium. The insurance companies start to use telematics and smart technologies to incentivize policyholders to exert preventive activities. As a result, current data availability could serve to promote self-protection and help policyholders to lower their exposure to risk, as will be examined in Chapter 4. A successful decrease in the high-risk agents' loss probability would then reduce the distance between different risk groups and their relative weight in the population.

3.6 Conclusion

Given current technological advances and the resulting accessibility of information, information symmetry becomes a relevant hypothesis. The extensive use of available data to price and tailor insurance contracts raise questions about the mutualization principle and solidarity.[19] Provided such a possibility, we explore the impact it would have on high-risk and low-risk agents, building on the common idea that insurers would be mainly interested in risk classification to offer lower prices to the low-risk agents.

In this chapter, we challenge the idea that the individualization of insurance premiums is advantageous for the stock insurers and low-risk agents. We assume that information is symmetrical due to the data availability on individual characteristics and actions, and, as a consequence, that it is possible to perfectly differentiate risk types.

We consider the stock insurer charging individualized insurance premiums, and the mutual insurer exerting less price differentiation. We also include in our analysis the second dimension of interest, which is the probability of insolvency. While mutual insurers can manage the possibility of insolvency ex-post by issuing a call for additional premiums, the stock insurers manage their probability of insolvency ex-ante by charging a risk loading on top of the pure premium. This allows the stock insurers to restrict the probability of insolvency to the desirable level, which

[18]Moreover, as demonstrated by Fagart et al. (2002), the contracts with both positive and negative premium adjustment are the efficient Pareto-optimal contracts.

[19]We discussed some of those questions in Chapter 1.

can be suggested by the regulator (0.5% at the European level).

We show that the low-risk agents are not necessarily better off with a stock insurance contract even if the stock insurer is informed about their low-risk type. For a given level of the probability of insolvency, the size of the stock insurance risk loading is determined by the number of policyholders. If the low-risk group is small, the associated size of the risk loading might provide low risks the incentive to join the mutual pool with the high-risk agents.

Needless to say, the actual choice between mutual and stock insurance might also depend on social preferences. Hence, the decision to choose mutual insurance can be determined by the preferences for solidarity or by the sense of personal engagement, rather than by the risk level itself. The mutual insurers may therefore be more efficient in promoting preventive activities, which is an interesting question for further research.

Considering prevention, our findings suggest that current data availability can serve to promote self-protection and help policyholders to lower their risk exposure. Such a possibility is examined in Chapter 4, where we compare in the experimental setting the classic experience-based contracts to the contracts based on the behavioral data on preventive activities.

Appendix B

B.1 Proof of Proposition 3.1

Proof of Proposition 3.1. Note that the stock insurance premium without the risk loading and the mutual insurance premium are identical for a homogeneous population and equal to $\pi = pL$. Consider a given value x of $\widetilde{X}$. Then, the agent's random wealth is:

$$\widetilde{w}^S|_{\widetilde{X}=x\leq p} = \widetilde{w}^M|_{\widetilde{X}=x\leq p} = (w-\pi, 1) \tag{B.1}$$

$$\widetilde{w}^S|_{\widetilde{X}=x>p} = (w-\pi, 1-x; w-\pi-L+\frac{\pi}{x}, x) \tag{B.2}$$

$$\widetilde{w}^M|_{\widetilde{X}=x>p} = (w-xL, 1) \tag{B.3}$$

Then, consider a lottery $\widetilde{\epsilon} = (xL-\pi, 1-x; xL-\pi-L+\frac{\pi}{x}, x)$. Note that we have:

$$\widetilde{w}^S|_{\widetilde{X}=x>p} = (w-xL+\widetilde{\epsilon}, 1) \tag{B.4}$$

$$= \widetilde{w}^M|_{\widetilde{X}=x>p} + \widetilde{\epsilon} \tag{B.5}$$

Given that $\mathbb{E}(\widetilde{\epsilon}) = 0$, $\widetilde{w}^S$ is a compound lottery that can be obtained from $\widetilde{w}^M$ by adding a zero-mean lottery to the state of the world corresponding to $x > p$. Thus, $\widetilde{w}^S$ is indeed a mean-preserving spread of $\widetilde{w}^M$ and will be preferred by all the risk-averse utility maximizers. □

B.2 Proof of Corollary 3.1

Proof of Corollary 3.1. Note that if each risk group chooses a different insurer, the resulting compositions of the mutual pool and the stock insurance portfolio stay homogeneous. In this case, the global risk in the mutual pool and in the stock insurance portfolio will depend on the risk distribution of the variable $\tilde{X}_k = \frac{\tilde{N}_k}{n_k}$, with $k = h, l$, and with N_h (N_l) the number of claimants of type h (l). In the absence of risk loading, the stock insurance premium and the mutual insurance premium for a homogeneous risk group of type k is equal to $\pi_k = p_k L$.

Consider that the risk group of type $k = h, l$ is in the mutual pool. Then, we can write the expected utility of wealth for the agent from the risk group of type k as

$$\mathbb{E}U(\tilde{w}^M) = U\Big(w - p_k L\Big) \Pr(\tilde{X}_k < p_k) + \int_{p_k}^{1} U\Big(w - xL\Big) f(x) dx \,.$$

If the risk group of type $k = h, l$ is covered by the stock insurer, we can write the expected utility of wealth for the agent from the risk group of type k as

$$\mathbb{E}U(\tilde{w}^S) = \int_0^1 xU\Big(w - p_k L - L + I(x)\Big) f(x) dx + \int_0^1 (1-x) U\Big(w - p_k L\Big) f(x) dx \,,$$

which can be rewritten as

$$\mathbb{E}U(\tilde{w}^S) = U\Big(w - p_k L\Big) - \int_0^1 x\Big[U\Big(w - p_k L\Big) - U\Big(w - p_k L - L + I(x)\Big)\Big] f(x) dx \,.$$

Given that the risk group of type k is homogeneous, $\overline{x} = p_k$ and $I(x) = L$ if $x \leq p_k$ and $I(x) = \frac{p_k L}{x}$ if $x > p_k$. Then, we can rewrite the previous expression as

$$\mathbb{E}U(\tilde{w}^S) = U\Big(w - p_k L\Big) - \int_{p_k}^1 x\Big[U\Big(w - p_k L\Big) - U\Big(w - p_k L - L + \frac{p_k L}{x}\Big)\Big] f(x) dx \,.$$

Recall from Proposition 3.1 that $\mathbb{E}U(\tilde{w}^M) > \mathbb{E}U(\tilde{w}^S)$, other things being equal. Hence, we have

$$\begin{aligned} &U\Big(w - p_k L\Big) \Pr(\tilde{X}_k < p_k) + \int_{p_k}^{1} U\Big(w - xL\Big) f(x) dx > \\ &\qquad U\Big(w - p_k L\Big) - \int_{p_k}^1 x\Big[U\Big(w - p_k L\Big) - U\Big(w - p_k L - L + \frac{p_k L}{x}\Big)\Big] f(x) dx \,. \end{aligned}$$

If the entire population of high-risk and low-risk agents is in the stock insurance portfolio, we have $\overline{x} = \theta p_h + (1-\theta) p_l$, and $I(x) = \frac{(\theta p_h + (1-\theta) p_l) L}{x}$, $\forall x > \overline{x}$. Then, a homogeneous group of k-type agents prefers the mutual insurer if

$$\begin{aligned} &U\Big(w - p_k L\Big) \Pr(\tilde{X}_k < p_k) + \int_{p_k}^{1} U\Big(w - xL\Big) f(x) dx > U\Big(w - p_k L\Big) - \\ &\int_{\theta p_h + (1-\theta) p_l}^1 x\Big[U\Big(w - p_k L\Big) - U\Big(w - p_k L - L + \frac{(\theta p_h + (1-\theta) p_l) L}{x}\Big)\Big] f(x) dx \,. \end{aligned}$$

Let (s_h, s_l) denote the strategy profile in terms of the choice of insurer made by the high-risk group and the low-risk group respectively. Let $\mathbb{E}U(\tilde{w}_k \,|\, (s_h, s_l))$ denote the expected utility of wealth for an agent of k type conditional on the strategy profile (s_h, s_l). Then, if $\theta \to 1\,, \theta p_h + (1-\theta)p_l \to p_h$, and we have

$$\mathbb{E}U(\tilde{w}_h^M \,|\, (M,S)) > \mathbb{E}U(\tilde{w}_h^S \,|\, (S,S))$$

The high-risk agents prefer to be insured by the mutual insurer rather then by the stock insurer insuring the low-risk agents as well. In the same way, if we have $\theta \to 0\,$, then $\theta p_h + (1-\theta)p_l \to p_l$, and in this case we also have

$$\mathbb{E}U(\tilde{w}_l^M \,|\, (S,M)) > \mathbb{E}U(\tilde{w}_l^S \,|\, (S,S))$$

Hence, by continuity, $\exists \theta > \hat{\hat{\theta}}$ such that $\mathbb{E}U(\tilde{w}_h^M \,|\, (M,S)) > \mathbb{E}U(\tilde{w}_h^S \,|\, (S,S))$, and $\exists \theta < \hat{\theta}$ such that $\mathbb{E}U(\tilde{w}_l^M \,|\, (S,M)) > \mathbb{E}U(\tilde{w}_l^S \,|\, (S,S))$. $\square$

B.3 Proof of Proposition 3.2

Proof of Proposition 3.2. From an application of Charpentier and Le Maux (2014), the expected utility under the stock insurance contract for a homogeneous population is given by

$$\mathbb{E}U(\tilde{w}^S) = \int_0^1 xU\left(w - \pi^S - L + I(x)\right) f(x)dx + \int_0^1 (1-x)U\left(w - \pi^S\right) f(x)dx\,,$$

which can be rewritten as

$$\mathbb{E}U(\tilde{w}^S) = U\left(w - \pi^S\right) - \int_0^1 x\Big[U\left(w - \pi^S\right) - U\left(w - \pi^S - L + I(x)\right)\Big] f(x)dx\,,$$

with $I(x) = L$ if $x \le \overline{x}$ and $I(x) = \frac{\pi^S}{x}$ if $x > \overline{x}$. Then, we can rewrite the expected utility expression as

$$\mathbb{E}U(\tilde{w}^S) = U\left(w - \pi^S\right) - \int_{\overline{x}}^1 x\Big[U\left(w - \pi^S\right) - U\left(w - \pi^S - L + \frac{\pi^S}{x}\right)\Big] f(x)dx\,,$$

where $\pi^S = p_k L + c\,$.

$$\frac{\partial \mathbb{E}U(\tilde{w}^S)}{\partial c} = -U'(w-\pi^S) - \frac{d}{dc}\int_{\overline{x}}^1 x\Big[U(w-\pi^S) - U(w - \pi^s - L + \frac{\pi^S}{x})\Big] f(x)dx\,.$$

From Leibniz rule, we have:

$$\begin{aligned}\frac{\partial \mathbb{E}U(\tilde{w}^S)}{\partial c} = -U'(w-\pi^S) - \int_{\overline{x}}^1 x\Big[& -U'(w-\pi^S) \\ & - \left(\frac{1}{x}-1\right)U'\left(w-\pi^s-L+\frac{\pi^S}{x}\right)\Big]f(x)dx \\ & + \frac{1}{L}\overline{x}\left[U(w-\pi^S)-U\left(w-\pi^S-L+\frac{\pi^S}{\overline{x}}\right)\right]f(\overline{x})\,,\end{aligned}$$

where $\frac{1}{L}=\frac{d\overline{x}}{dc}$. Since $\frac{\pi^S}{\overline{x}}=L$, we have:

$$\begin{aligned}\frac{\partial \mathbb{E}U(\tilde{w}^S)}{\partial c} &= -U'(w-\pi^S) \\ &\quad - \int_{\overline{x}}^1 x\Big[-U'(w-\pi^S)+\left(1-\frac{1}{x}\right)U'\left(w-\pi^s-L+\frac{\pi^S}{x}\right)\Big]f(x)dx \\ &= -U'(w-\pi^S)+\int_{\overline{x}}^1\left[xU'(w-\pi^S)+(1-x)U'\left(w-\pi^s-L+\frac{\pi^S}{x}\right)\right]f(x)dx\end{aligned}$$

Using Taylor development, we have $f(x)\approx f(a)+f'(a)(x-a)$. For $a=w-\pi^S$, we have:

$$U'(w-\pi^S-L+\frac{\pi^S}{x})\approx U'(w-\pi^S)+(-L+\frac{\pi^S}{x})U''(w-\pi^S)\,,$$

or else

$$(1-x)U'(w-\pi^S-L+\frac{\pi^S}{x})+xU'(w-\pi^S)\approx U'(w-\pi^S)+(1-x)(-L+\frac{\pi^S}{x})U''(w-\pi^S)\,.$$

Consequently,

$$\begin{aligned}\frac{\partial \mathbb{E}U(\tilde{w}^S)}{\partial c} &= -U'(w-\pi^S)+\int_{\overline{x}}^1\left[xU'(w-\pi^S)+(1-x)U'\left(w-\pi^s-L+\frac{\pi^S}{x}\right)\right]f(x)dx \\ &= -U'(w-\pi^S)+\int_{\overline{x}}^1\left[U'(w-\pi^S)+(1-x)(-L+\frac{\pi^S}{x})U''(w-\pi^S)\right]f(x)dx\,,\end{aligned}$$

which we can rewrite as:

$$\begin{aligned}\frac{\partial \mathbb{E}U(\tilde{w}^S)}{\partial c} = -U'(w-\pi^S)+U'(w-\pi^S)\int_{\overline{x}}^1 & f(x)dx+ \\ \int_{\overline{x}}^1 & (1-x)(-L+\frac{\pi^S}{x})U''(w-\pi^S)f(x)dx\,.\end{aligned}$$

Given that $\int_{\overline{x}}^1 f(x)dx = 1-\Pr(\tilde{X}\leq\overline{x})$, we have:

$$\frac{\partial \mathbb{E}U(\tilde{w}^S)}{\partial c} = -U'(w-\pi^S)\Pr(\tilde{X}\leq\overline{x})+U''(w-\pi^S)\int_{\overline{x}}^1(1-x)(-L+\frac{\pi^S}{x})f(x)dx\,.$$

Since $I(x) = \frac{\pi^S}{x}$ for $x > \overline{x}$ and $I(x) = L$ otherwise, we can write:

$$\int_{\overline{x}}^{1} (1-x)(-L + \frac{\pi^S}{x}) f(x) dx = -\int_{\overline{x}}^{1} (1-x)(I(\overline{x}) - I(x)) f(x) dx = -H(\overline{x}) \, ,$$

where $H(\overline{x})$ is a positive function such that $\frac{\partial H(\overline{x})}{\partial \overline{x}} < 0$. Then we have:

$$\frac{\partial \mathbb{E} U(\tilde{w}^S)}{\partial c} = -U'(w - \pi^S) \Pr(\tilde{X} \leq \overline{x}) - U''(w - \pi^S) H(\overline{x}) \, .$$

The impact of the risk loading on the expected utility of wealth is negative if $\frac{\partial \mathbb{E} U(\tilde{w}^S)}{\partial c} < 0$, which is the case when $-U'(w-\pi^S) \Pr(\tilde{X} \leq \overline{x}) - U''(w-\pi^S) H(\overline{x}) < 0$, leading to the following condition:

$$\frac{\Pr(\tilde{X} \leq \overline{x})}{H(\overline{x})} > -\frac{U''(w - \pi^S)}{U'(w - \pi^S)} \, ,$$

where the right term is the Arrow-Pratt measure of risk aversion.

The left term in the condition above is always positive, while the right term is positive if the utility function U is concave, which means that it is positive for any risk-averse expected utility maximizer. Nevertheless, the condition above is not necessarily verified, since the left term is not necessarily greater than the value of the Arrow-Pratt measure of risk aversion. Given that $\frac{\Pr(\tilde{X} \leq \overline{x})}{H(\overline{x})}$ is increasing with $\overline{x}$, $\frac{\partial \mathbb{E} U(\tilde{w}^S)}{\partial c} < 0$ when $\overline{x}$ is large, and $\frac{\partial \mathbb{E} U(\tilde{w}^S)}{\partial c} > 0$ when $\overline{x}$ is small. Consequently, there exists an inflection point $\hat{x}$ such that when $\overline{x} < \hat{x}$, $\frac{\partial \mathbb{E} U(\tilde{w}^S)}{\partial c} > 0$. $\square$

Chapter 4

Behavioral contract or bonus-malus contract for improving prevention: an experimental approach

This chapter is the basis of the article "*Behavioral contract or bonus-malus contract: an experimental approach*", co-authored with Meglena Jeleva and Mathieu Lefebvre

Summary of the chapter

The recent use of telematics data related to the policyholder's behavior makes it possible, in theory, to tie the automobile insurance premiums to the preventive effort rather than claims history, as it is the case with a bonus-malus system. To our knowledge, no experimental study has been conducted neither on the incentives for prevention of the bonus-malus contracts nor on the comparison between the latter and the new contract types based on the individual behavior. We develop a theoretical model of optimal prevention effort under two contract types and design an experiment to test our predictions on how the contract type affects the policyholders' self-protection effort, as well as on the preferences towards one type or another. We find that the subjects choosing a behavioral contract provide higher levels of prevention effort than the subjects choosing a bonus-malus contract. Moreover, the contract choice seems to be determined by the individual preferences for prevention. We also find that the risk-seeking subjects provide less effort to decrease their loss probability, and the same holds true for the more prudent subjects.

Key words: behavior, bonus-malus, experiment, prevention, self-protection

JEL classification: C91, D81, G22

4.1 Introduction

New data and new technologies provide a possibility to create new types of insurance contracts. In particular, new technologies of data collection such as telematics or smart devices are currently used to gather information on the policyholders' individual behavior. This information can be used to provide personal advice on risk mitigation, and even to offer discounts based on the desirable level of preventive activities. The insurance contracts taking into account the policyholders' prevention activity already exist in some forms, and the insurance sector where the use of individual behavior finds the most advanced development is the automobile insurance sector.

The automobile insurance based on the policyholder's car usage or driving behavior is known as UBI. The UBI contracts include the insurance coverage based on the actual usage, such as the insurance coverage based on kilometers driven (PAYD), or the insurance coverage based on the driving behavior estimated from the data collected through the black boxes (PHYD).[1] In the case of PHYD insurance, telematics data includes information such as driving speed, harsh braking, acceleration, cornering, or time of the day the journey is made. This data is analyzed to calculate driving "scores" based on the indicators of driving behavior collected through the telematics devices. Those scores are further used by insurers to offer discounts to the policyholders showing good driving behavior.

An American insurer Metromile offering a distance-based PAYD insurance has recently started to offer a free insurance quote based on the telematics data. Users can download a smartphone application that tracks their mileage and other driving data during two following weeks. Then it calculates a free estimation for their potential insurance premium and the coverage suitable for their needs. Another example is the UK insurer Cuvva who offers PAYD insurance coverage since 2016. Cuvva has recently launched a new flexible pay-monthly motor insurance coverage which can be canceled at any time.

The largest markets for telematics insurance are the US, Canada, Italy, and the UK. In Europe, more than 50% of telematics insurance contracts are offered by the Italian insurers UnipolSai and Generali. Italy represents one of the biggest European markets for telematics insurance because the Italian legislation recommends the installation of telematics devices to all car insurance providers since 2017. The Italian Insurance Association estimates that telematics boxes have been installed in over 2 million cars in Italy (OECD, 2017).

[1] Some examples of such contracts are provided in Chapter 1.

The application of behavioral data in the automobile insurance sector is particularly interesting because the automobile insurance contracts often include a premium calculation scheme that is experience-based. An experience-based system implies that the insurance premium is adjusted according to the individual claims experience upon renewal. In France, the experience-based rating system currently used in automobile insurance is called *bonus-malus* system.

To our knowledge, no experimental study has been conducted on the incentives for the prevention of such experience-based contracts. Indeed, from the theoretical point of view, one of the reasons behind an experience-based system is to promote preventive activity. There exists empirical literature that uses real insurance data and aims to disentangle the potential effect of preventive incentives from various sources of information asymmetry, such as adverse selection and learning (Abbring, Chiappori, and Pinquet, 2003; Abbring, Chiappori, and Zavadil, 2008; Dionne, Michaud, et al., 2013). We use the experimental setting to explicitly identify the individual investment in prevention effort and to control for relevant individual characteristics that can influence the provision of prevention efforts, such as risk aversion or prudence.

Moreover, to our knowledge, our paper is the first to examine the insurance contracts fully based on the preventive behavior and the first to compare this new contract type to the more common experience-based contract. Currently, the European legislation only allows using rewards and discounts based on individual behavior. Nevertheless, given the fast development of new technologies and new products, one can easily imagine an insurance contract entirely based on the policyholders' preventive behavior rather than claims history, or at least allowing for both positive and negative premium adjustments, rather than discounts and rewards alone.

From the actuarial point of view, it is suggested that behavioral data and driving scores should be added to the standard variables used in the calculation of the credibility factor in the experience-based system (Denuit, Guillen, et al., 2019). One can imagine that the score of preventive behavior could replace the pricing based on the accidents, if the former is considered more "fair", for example. Thus, we also aim to explore the question of preferences towards one contract or another, since the contract choice can be based on economic rationality, personal situation, individual preferences, or even ideological beliefs.

In the present chapter, we, therefore, address two issues. First, we examine how the contract type affects the policyholders' preventive actions, namely the effort provided to reduce the probability of an accident. Second, we study the contract choice and its potential determinants.

We begin by developing a theoretical model of optimal prevention effort under two contracts, a bonus-malus contract and a behavioral contract. Then, we derive our predictions and hypotheses that are further used to design the experimental procedure. The main experiment consists in individual decisions regarding the prevention effort, given a bonus-malus contract. In the middle of the main experiment, subjects can switch to the behavioral contract or stay with a bonus-malus contract. Thus, we can explore both the prevention effort under two contract types and the choice of contact.

We use an adapted multiple-price list (Drichoutis and Lusk, 2016) to elicit risk aversion in the gain and loss domains. In addition, we elicit the subjects' absolute risk aversion by comparing their switch point in two identical multiple-price lists with a different initial endowment. We also elicit prudence in the loss domain (Noussair et al., 2014; Brunette and Jacob, 2019), given that prudence is known to be an important determinant of prevention effort.

Our findings support some of our predictions. Namely, the subjects choosing a behavioral contract provide higher levels of prevention effort than the subjects choosing a bonus-malus contract. We also observe self-selection according to the individual preferences for prevention. Precisely, the subjects providing a higher level of effort in the first part of the experiment choose to continue with a behavioral contract. Nevertheless, we find that the choice of contract type is a significant determinant of the provision of prevention effort, even if we control for the average level of effort provided during the first part of the experiment.

Considering the impact of an accident on the prevention effort in the following period, our findings are not clear. The loss occurrence is a significant determinant of the effort in the first part of the game, but less so in the second part. Besides, our results also confirm the theoretical findings that the prevention effort depends on risk aversion and prudence. In particular, we find that risk-seeking individuals provide less effort to decrease their loss probability, and the same holds for more prudent subjects.

This chapter is organized as follows. In Section 4.2 we review the literature relevant for our research question, namely the theoretical literature on self-protection and the literature on bonus-malus systems. We proceed by developing a theoretical model of optimal prevention effort under two contracts, a bonus-malus contract and a behavioral contract, in Section 4.3, where we also derive our predictions and testable hypotheses for the experiment. The experimental design is presented in Section 4.4, where we describe our main experiment, elicitation tasks, and procedures. We present our results in Section 4.5, beginning with a non-parametric analysis and proceeding further with some relevant econometric regressions. Section 4.6 concludes.

4.2 Related literature

To our knowledge, there exists no literature that addresses experimentally neither the incentives for prevention provided by bonus-malus contracts nor the comparison of such contracts with the behavioral contracts based on the observable prevention effort.

There exists experimental literature related to other insurance contexts, for instance regarding the demand for insurance (Corcos et al., 2017; Robinson and Botzen, 2019), the self-insurance (Pannequin et al., 2019; Mol et al., 2020), or the willingness to pool or to pay for mutual insurance (Gajdos et al., 2014; Mimra, Nemitz, et al., 2019). There also exists experimental literature on prevention effort in general, and in particular related to prudence (Krieger and Mayrhofer, 2017; Masuda and E. Lee, 2019).

We choose to present two different strands of literature that are more closely related to the questions we address in the present chapter. First, the theoretical literature on prevention, and in particular on self-protection. Second, the literature on bonus-malus contracts in relation to prevention.

4.2.1 Prevention effort and self-protection

In addition to insurance as a tool to cope with the risk, there exist two other mechanisms for risk prevention: self-insurance and self-protection. We are interested in self-protection, also called loss prevention, which refers to the actions that modify the probability of the loss (Courbage, Rey, and Treich, 2013).

Ehrlich and Becker (1972) were the first to examine the interactions between those three tools: market insurance, self-insurance, and self-protection. They show that market insurance and self-protection could be complements, depending for instance on the initial loss probability. Yet, the issue that has produced the most development in the literature on self-protection is its link with risk aversion. Indeed, more risk-averse agents prefer less risky activities, but as the following findings show, risk-averse agents do not always prefer more self-protection.

Precisely, an increase in risk aversion does not necessarily imply an increase in self-protection. As Dionne and Eeckhoudt (1985) show in the specific case of quadratic utility functions, more risk aversion induces more self-protection only if the initial loss probability is lower than 0.5. The intuitive explanation for this result, provided later by Eeckhoudt and Gollier (2005), is that more self-protection can actually increase risk if the loss probability is already very high.[2] This result is extended to the more general case by Briys and Schlesinger (1990), who show that the same holds true in the case of the state-dependent utility functions or a random initial wealth. Moreover, they highlight an important observation concerning self-protection, namely that self-protection decreases income in both loss and no loss states, implying that the risk is not necessarily reduced by investment in self-protection.[3]

Those ambiguous results persist if one considers the willingness to pay to reduce the probability of loss rather than an investment in self-protection, as shown by Eeckhoudt, Godfroid, et al. (1997): the willingness to pay might increase or decrease with risk aversion, depending on the individual preferences.[4] Indeed, the conclusions are heavily dependent on multiple factors, such as individual preferences, the initial level of loss probability, and the effectiveness of prevention technology. A series of findings show that self-protection increases with risk aversion if and only if the initial loss probability is low enough and in particular lower than a utility-dependent threshold (Jullien et al., 1999; Dachraoui et al., 2004; Eeckhoudt, Gollier, and Schlesinger, 2011).[5] We obtain similar results, as we will show in Section 4.3.

As we mentioned previously, an important source of ambiguous results arises from the fact that self-protection decreases wealth in both loss and no-loss states. This implies a strong link with the downside risk aversion and the notion of prudence. Eeckhoudt and Gollier (2005) introduce prudence in their study on self-protection and show that a risk-averse and prudent individual invests less than a risk-neutral individual (non-prudent by definition) if the optimal investment of the latter is at least as high as 0.5.[6] To obtain a more clear effect of risk aversion and prudence on self-protection, it is necessary to specify the loss probability and the form of utility

[2]As Eeckhoudt and Gollier (2005) explain, if it is optimal for the risk-neutral agent not to exert any effort, so that the accident will be incurred with certainty, exerting effort would induce risk since the probability of accident will be less than unity, which is not desirable for risk-averse agents.

[3]As the authors further develop, it means that self-protection does not reduce risk in the Rothschild and Stiglitz (1970) sense. In particular, a higher level of self-protection simultaneously induce a mean-preserving spread in the states with lower wealth, and a mean-preserving contraction in the states with higher wealth.

[4]For example, a risk-averse agent with CARA utility function can have a higher willingness to pay than a risk-neutral individual.

[5]The utility-dependent threshold derived by Jullien et al. (1999) is equal to 0.5 in the special case of quadratic utility functions.

[6]This is explained by the fact that prudent individuals prefer to increase their savings in case they are in the loss state, rather than invest in self-protection. Similar results are obtained by Dachraoui et al. (2004) and Dionne and Li (2011).

function (Dachraoui et al., 2004; Eeckhoudt and Gollier, 2005; Alary et al., 2013). We will return to this point in Section 4.3.

Another factor that determines the effect of risk aversion on self-protection is the effectiveness of prevention technology. As Courbage and Rey (2008) show in the case of small risks, the willingness to pay for self-protection increases with risk aversion if the initial loss probability is inferior to 0.5 . And more importantly, when the loss probability is superior to 0.5 , the authors show that the higher it is, the more efficient the prevention technology has to be to increase the willingness to pay for self-protection.

Recently, some authors have shown that the complex impact of individual preferences on self-protection stems from the multiplicity of channels through which self-protection affects the agents' utility. Crainich, Eeckhoudt, and Hammitt (2015) show that in case of risk aversion, the willingness to pay to reduce the probability of loss is a product of the willingness to pay under risk neutrality and an adjustment factor that depends both on risk aversion and on downside risk aversion. Denuit, Eeckhoudt, Liu, et al. (2016) show that an increase in self-protection can be decomposed into an increase in downside risk and a residual stochastic change, which depends on the parameter values of self-protection and can be positive or negative. Thus, a prudent agent will choose a higher level of self-protection only if the latter outweighs the negative impact that an increase in downside risk has on the agent's expected utility.[7]

Given this theoretical evidence, it appears that there is no clear-cut link between individual preferences and the optimal level of self-protection.[8] Our theoretical predictions established in Section 4.3 confirm the difficulty to derive direct testable hypotheses without specifying some functional forms and parameters.

4.2.2 Bonus-malus contract and experience-rating systems

Experience-rating systems, also known as credibility systems or bonus-malus systems, allow employing what is called an *a posteriori* pricing of insurance contracts. The *a priori* pricing implies risk classification based on observable variables that

[7]Overall, Denuit, Eeckhoudt, Liu, et al. (2016) confirm that more prudent agents *tend* to choose less self-protection.

[8]Some other literature on the determinants of self-protection includes the interaction between prudence and savings (Menegatti, 2009; Menegatti and Rebessi, 2011; Eeckhoudt and Spaeter, 2013; Hofmann and Peter, 2016; Peter, 2017), self-protection investment when more than two states of the world are possible (D. J. Meyer and J. Meyer, 2011), the impact of background risk or of the presence of multiple risks on self-protection (K. Lee, 2012a; Courbage and Rey, 2012; Eeckhoudt, Huang, et al., 2012; Courbage, Loubergé, et al., 2017), or the impact of ambiguity aversion on self-protection decision (Snow, 2011; Alary et al., 2013).

are supposed to reflect the individual risk (age, vehicle type, geographical zone), while the a posteriori pricing allows to better tune the price ex-post, by taking into account the individual experience.

Thus, the bonus-malus system and related contracts have two objectives (Lemaire, 1995). First, they allow reevaluating the risk on the basis of claims history and individual risk experience, which are supposed to reveal some relevant unobserved information. Next, it also allows providing incentives for risk prevention through the system of rebates (bonuses) and surcharges (maluses) (Boyer and Dionne, 1989; Dionne and Lasserre, 1985; Dionne and Vanasse, 1992; Chiappori et al., 1994). Overall, the use of bonus-malus systems can be explained by adverse selection, moral hazard, and learning (Charpentier, 2010).

There exists empirical literature that focuses on testing real insurance data for the evidence of prevention incentives provided by a bonus-malus system, by searching for the presence of the moral hazard. In particular, under the moral hazard hypothesis, theoretical findings predict that the prevention effort should increase after the occurrence of an accident. Namely, a declared accident implies a surcharge, which increases the marginal cost of future claims. This increase in marginal cost makes it optimal to provide a higher prevention effort in the following periods.

Yet, the use of empirical insurance data provided by a bonus-malus system and aiming to examine the presence of prevention incentives involves a series of practical and conceptual difficulties. First, it is necessary to separate the effect of moral hazard from other sources of information asymmetry, such as adverse selection and learning.[9] Recent empirical studies intend to deal with the issue of separating moral hazard from adverse selection and learning by analyzing dynamic data, concluding with heterogeneous findings nevertheless (Abbring, Chiappori, and Pinquet, 2003; Abbring, Chiappori, and Zavadil, 2008; Dionne, Pinquet, et al., 2011; Dionne, Michaud, et al., 2013).

Another issue that appears when dealing with empirical insurance data is the difficulty to distinguish between claims and accidents.[10] In other words, insurance data includes only the information on claims. Thus, if one measures the prevention effort as the probability of having accidents in the future, it is important to distin-

[9]Adverse selection would imply a positive link between past claims and the probability of future claims. Moral hazard implies a negative link because a past claim would imply a lower probability of future claims. Learning also implies a negative link, because a young driver could learn from the experience and adjust his or her behavior after an accident according to the new knowledge. It is difficult to conclude without distinguishing properly those two phenomena.

[10]As noted by Abbring, Chiappori, and Pinquet (2003), there are three main problems needed to be addressed in empirical studies with real data: the learning effect, which goes in the same sense that the moral hazard and thus prevention incentives, the impossibility to distinguish between accidents and claims, and the fact that premiums are not continuously adjusted in reality.

guish a decrease in claims probability due to the prevention effort from a decrease due to the non-declaration of small accidents. The phenomenon of non-declaration of small accidents is known as “hunger for bonuses” (Lemaire, 1995; Henriet and Rochet, 1986; Charpentier, David, et al., 2017).

The experimental setting and the comparison of bonus-malus contract and behavioral contract allow us to exclude the adverse selection issue and to control for multiple important characteristics, such as risk aversion and prudence. It also allows us to potentially isolate monetary incentives from other possible non-monetary ones, given that behavioral contract does not imply a surcharge in case of an accident, as will be further explained in the rest of this chapter.

It should be noted that we use a simplified version of a bonus-malus contract, with no accumulation of rebates or surcharges. In fact, we opt for a simplified system because we want to reduce the impact of wealth variations on individual decisions, since we are interested in the comparison of prevention efforts under bonus-malus and behavioral contracts. The system that we model in this chapter is indeed not an optimal version of an experience-based system. Nevertheless, the real systems effectively implemented today are also very different from the optimal bonus-malus contracts described in theoretical literature (Henriet and Rochet, 1986; Rubinstein and Yaari, 1983).[11]

The French bonus-malus system is currently at its stationary point, meaning that the proportion of drivers at the maximum possible level of bonus scale is constant since 2006, the 30 years anniversary of the introduction of this system (Charpentier, 2010). Consequently, the “good” drivers have no more incentives to exert preventive behavior, and this is one of the reasons why insurers are trying to invent new ways of providing incentives to the policyholders, such as life bonuses or behavioral discounts. At the same time, some solutions, such as a life bonus, might induce adverse behavior, since those who are close to the maximum possible bonus have incentives not to declare their accidents, or to drive carelessly once the life bonus is obtained. Thus, it is particularly relevant in the current context to evaluate other possible mechanisms of incentives provision, such as contracts based on the preventive behavior, as we do in the present chapter.

[11] For instance, the French bonus-malus system is too simple from the theoretical point of view. The theory suggests that an optimal bonus-malus system should use a non-uniform rebate/surcharge coefficient (“*coefficient de réduction-majoration*” in french).

4.3 Prevention decisions with two contract types

4.3.1 The model of prevention with two contract types

Consider an agent living for $T = 2$ periods. The agent is endowed with a non-random initial wealth w at each period and faces a risk of losing a monetary amount L , $L < w$, following the occurrence of an accident. The individual preferences are represented by the EU model and are assumed to be time-separable.

The occurrence of an accident during the period t, $t = 1, 2$, is determined by the initial loss probability p_0. The agent can decrease the initial loss probability by providing a positive level of prevention effort, which is costly nevertheless. We denote e_t the level of prevention effort that the agent chooses to provide for the period t, $e_t \in [0, \bar{e}]$. We suppose that the effort level e_t affects the loss probability for the period t only. The resulting loss probability $p(e)$ is decreasing and convex with the level of effort: $p'(e) < 0, p''(e) > 0$, with $p(0) = p_0$. The cost of prevention effort $c(e)$ is increasing and convex with the level of effort: $c'(e) > 0, c''(e) > 0$, with $c(0) = 0$.

We suppose that insurance is mandatory. Hence, the agent has to choose between two types of insurance contracts, a “behavioral” contract (BC) and a “bonus-malus” contract (BM). Both contracts provide partial coverage: there is a deductible D such that the indemnity is $L - D$ in case of loss.

The insurance premium for the period t is denoted Π_t and its structure depends on the contract type, as we will explain below. To simplify, we assume that the premium does not involve any loading factor.

Behavioral contract

In the case of the behavioral contract, the level of prevention effort that the agent chooses to provide during the period t is observable by the insurer, and it is taken into account for the premium calculation in the next period. Thus, the premium for the period $t + 1$ is set according to the effort provided during the previous period. Precisely, for all $t > 1$, $\Pi_{t+1} = p(e_t)(L - D)$.

We suppose that the premium paid for the first period is based on the average possible level of effort, since the insurer has no information yet on the level of effort provided at the beginning: $\Pi_1 = p(\frac{\bar{e}}{2})(L - D)$. Hence, assuming $T = 2$, the agent chooses the couple of effort levels (e_1, e_2) that maximizes the agent’s expected utility denoted $V(e_1, e_2)$.

Given the time-separability of individual preferences, we can write:

$$\begin{aligned}
V(e_1, e_2) &= Eu(e_1) + \delta Eu(e_1, e_2) \qquad (4.1)\\
&= p(e_1)u\Big(w - D - c(e1) - \Pi_1\Big) + \Big(1 - (p(e_1)\Big)u\Big(w - c(e_1) - \Pi_1\Big)\\
&+ \delta\Big[p(e_2)u\Big(w - D - c(e_2) - \Pi_2\Big) + \Big(1 - p(e_2)\Big)u\Big(w - c(e_2) - \Pi_2\Big)\Big]
\end{aligned}$$

where δ is the time discounting factor. For simplicity, in what follows we assume that δ is equal to 1.

Bonus-malus contract

In the case of the bonus-malus contract, the effort level is assumed unobservable by the insurer. The premium for the period $t+1$ is conditional on the loss realization during the period t. Precisely, if the loss is realized during the period t, the agent pays the highest premium for the period $t+1$, since the insurer assumes that no effort was provided, and the lowest premium otherwise. Therefore, we have $\forall t > 1$, $\Pi_{t+1} = p_0(L - D) = \Pi^{max}$ if the agent had an accident during the period t, and $\Pi_{t+1} = p(\bar{e})(L - D) = \Pi^{min}$ otherwise. We suppose that the premium paid for the first period is based on the average possible level of effort since the insurer has no information on the accident history: $\Pi_1 = p(\frac{\bar{e}}{2})(L - D)$.

The accident occurrence affects the agent's wealth in the following period through the premium level. Thus, the agent can potentially choose different effort levels in period $t+1$ according to the occurrence of an accident in period t. We denote e^S_{t+1} and $e^{\overline{S}}_{t+1}$ the effort levels given that the accident has or has not occurred respectively during the period t. Consequently, assuming $T = 2$, the agent chooses the vector of effort levels $(e_1, e^S_2, e^{\overline{S}}_2)$ that maximizes the agent's expected utility denoted $V(e_1, e^S_2, e^{\overline{S}}_2)$. Given the time-separability of individual preferences, we can write:

$$\begin{aligned}
V(e_1, e^S_2, e^{\overline{S}}_2) &= Eu(e_1) + \delta\Big(p(e_1)Eu(e^S_2) + (1 - p(e_1))Eu(e^{\overline{S}}_2)\Big) \qquad (4.2)\\
&= p(e_1)u(w - D - c(e_1) - \Pi_1) + (1 - p(e_1))u(w - c(e_1) - \Pi_1)\\
&+ \delta\Bigg[p(e_1)\Big(p(e^S_2)u(w - D - c(e^S_2) - \Pi^{max})\\
&+ (1 - p(e^S_2))u(w - c(e^S_2) - \Pi^{max})\Big)\\
&+ (1 - p(e_1))\Big(p(e^{\overline{S}}_2)u(w - D - c(e^{\overline{S}}_2) - \Pi^{min})\\
&+ (1 - p(e^{\overline{S}}_2))u(w - c(e^{\overline{S}}_2) - \Pi^{min})\Big)\Bigg],
\end{aligned}$$

with δ the time discounting factor that we assume to be equal to 1.

4.3.2 Optimal prevention level

In the following, we determine the optimal levels of prevention for each type of contract and the impact of some prevention technology characteristics on these prevention levels.

Optimal effort with a behavioral contract

The optimal prevention levels e_1 and e_2 are solutions of the following maximization problem:

$$Max_{e_1,e_2} V(e_1, e_2)$$

$$V(e_1, e_2) = p(e_1)u(A_1) + (1 - p(e_1))u(B_1) + p(e_2)u(A_2) + (1 - (p(e_2))u(B_2),$$

with A_t the final wealth in period t in case of an accident, and B_t the final wealth in period t if there is no accident,

$$\begin{aligned} A_1 &= w - D - c(e_1) - p(\bar{e}/2)(L - D) \\ B_1 &= w - c(e_1) - p(\bar{e}/2)(L - D) \\ A_2 &= w - D - c(e_2) - p(e_1)(L - D) \\ B_2 &= w - c(e_2) - p(e_1)(L - D) \end{aligned}$$

The assumptions regarding the cost function $c(e)$ and the probability function $p(e)$ are not sufficient to ensure that the second-order conditions for a maximum are satisfied. Following the theoretical literature on self-protection, we assume for the sake of simplicity that the functions V , c and p , as well as the parameters involved, are such that the second-order conditions are verified, and there exists a unique solution for the maximization problem for each period such that the first-order conditions (FOC) are verified (Jullien et al., 1999; Courbage, Rey, and Treich, 2013). For instance, the following assumption guarantees that the function of two variables is concave and that the second-order conditions are verified:

Assumption A1. *For all $e_1 \geq 0$, $e_2 \geq 0$, we have:*

$$\begin{gathered} V_{e_1e_1} < 0, V_{e_2e_2} < 0 \\ V_{e_1e_1}V_{e_2e_2} - (V_{e_1e_2})^2 > 0, \end{gathered}$$

with index i denoting the first derivative with regards to the i^{th} argument and index ii the second derivative.

Let us also remark that expression $V_{e_1 e_2}$ can be positive or negative depending on individual preferences and prevention technology.

For a risk-averse agent with a concave utility function, $u(.)' > 0\,, u(.)'' < 0\,$, the first-order conditions for the optimal effort level, e_t^*, write:

$$-c'(e_1^*)\Big(p(e_1^*)u'(A_1) + (1-p(e_1^*))u'(B_1)\Big) = \tag{4.3}$$
$$\underbrace{p'(e_1^*)\Big(u(B_1) - u(A_1)\Big)}_{(1)} + \underbrace{p'(e_1^*)(L-D)\Big(p(e_2)u'(A_2) + (1-p(e_2))u'(B_2)\Big)}_{(2)}$$
$$-c'(e_2^*)\Big(p(e_2^*)u'(A_2) + (1-p(e_2^*))u'(B_2)\Big) = p'(e_2^*)\Big(u(B_2) - u(A_2)\Big) \tag{4.4}$$

In both cases, the optimal effort level is such that the marginal cost equals the marginal benefit of the prevention. While the marginal cost is the same for both periods, the marginal benefit is different. In Eq. (4.3), the first term on the right, denoted by (1), represents the marginal benefit of prevention effort in terms of the loss probability reduction. In other words, it illustrates the marginal benefit from a decrease in the chances of paying a deductible. The second term on the right, denoted by (2), represents the marginal benefit of the prevention effort related to the decrease in premium for the following period.[12] For the second period (Eq. (4.4)), the marginal benefit associated with a decrease in premium is absent, since the second period is the last one. Thus, by construction, the optimal effort level is always lower in the second period, compared to the first one.[13]

Consider now a risk-neutral agent with a linear utility function $u(w) = w$. The first-order conditions for the optimal effort levels for a risk-neutral agent, e_t^n, write:

$$-\,c'(e_1^n) = p'(e_1^n)L \tag{4.5}$$
$$-\,c'(e_2^n) = p'(e_2^n)D \tag{4.6}$$

As we can see from Eq. (4.5) and Eq. (4.6), the optimal effort levels in two periods are independent for a risk-neutral agent, as opposed to the case of a risk-averse agent.[14]

[12]The details of derivation are provided in Appendix C.1.

[13]Or, more generally, the optimal effort level is always lower in the last period than in the previous one.

[14]Note that the general form for Eq. (4.5) is $-c'(e_1^n) = p'(e_1^n)(D + \delta(L-D))$.

Optimal effort with a bonus-malus contract

The optimal prevention levels e_1, e_2^S and $e_2^{\overline{S}}$ are solutions of the following maximization problem:

$$Max_{e_1,e_2^S,e_2^{\overline{S}}} V(e_1, e_2^S, e_2^{\overline{S}})$$

$$\begin{aligned} V(e_1, e_2^S, e_2^{\overline{S}}) &= p(e_1)u(A_1) + (1-p(e_1))u(B_1) \\ &+ p(e_1)\Big(p(e_2^S)u(A_2^S)) + (1-p(e_2^S))u(B_2^S)\Big) \\ &+ (1-p(e_1))\Big(p(e_2^{\overline{S}})u(A_2^{\overline{S}}) + (1-p(e_2^{\overline{S}}))u(B_2^{\overline{S}})\Big) \end{aligned}$$

with A_t the final wealth in period t in case of an accident, B_t the final wealth in period t if there is no accident, and with the superscript S ($\overline{S}$) denoting the occurrence (or not) of an accident during the previous period:

$$\begin{aligned} A_1 &= w - D - c(e_1) - p(\bar{e}/2)(L-D) \\ B_1 &= w - c(e_1) - p(\bar{e}/2)(L-D) \\ A_2^S &= w - D - c(e_2^S) - p_0(L-D) \\ B_2^S &= w - c(e_2^S) - p_0(L-D) \\ A_2^{\overline{S}} &= w - D - c(e_2^{\overline{S}}) - p(\bar{e})(L-D) \\ B_2^{\overline{S}} &= w - c(e_2^{\overline{S}}) - p(\bar{e})(L-D) \end{aligned}$$

The first-order conditions for the optimal effort level of a risk-averse agent are:

$$-c'(e_1^*)\Big(p(e_1^*)u'(A_1) + (1-p(e_1^*))u'(B_1)\Big) = \tag{4.7}$$

$$p'(e_1^*)\Big(u(B_1) - u(A_1)\Big) + p'(e_1^*)\Big(Eu(e_2^{\overline{S}}) - Eu(e_2^S)\Big)$$

$$-c'(e_2^{S*})\Big(p(e_2^{S*})u'(A_2^S) + (1-p(e_2^{S*}))u'(B_2^S)\Big) = p'(e_2^{S*})\Big(u(B_2^S) - u(A_2^S)\Big) \tag{4.8}$$

$$-c'(e_2^{\overline{S}*})\Big(p(e_2^{\overline{S}*})u'(A_2^{\overline{S}}) + (1-p(e_2^{\overline{S}*}))u'(B_2^{\overline{S}})\Big) = p'(e_2^{\overline{S}*})\Big(u(B_2^{\overline{S}}) - u(A_2^{\overline{S}})\Big) \tag{4.9}$$

The optimal effort levels in two periods are not independent, as was the case with a behavioral contract.[15] Besides, the difference between Eq. (4.8) and Eq. (4.9) is determined by the difference in wealth levels. Indeed, for an agent with a bonus-malus contract, a loss in period $t-1$ can affect the optimal effort in period t through the changes in premium level, adjusted based on the accident occurrence.

[15]The details of computations are provided in Appendix C.1.

For a risk-averse agent, the impact of a change in wealth on the optimal level of self-protection depends on the magnitude of variations of loss probability $p(e^*)$ and on the degree of absolute risk aversion, in particular on the Arrow-Pratt measure of absolute risk aversion, $-{u''(\cdot)}/{u'(.)}$ (Sweeney and Beard, 1992; K. Lee, 2005). For instance, for a CARA agent, the variations of wealth do not affect the optimal level of effort. For DARA and IARA agents, the results are ambiguous. In particular, as Sweeney and Beard (1992) show, both DARA and IARA agents might invest more in self-protection following an increase in initial wealth.[16]

The first-order conditions for the optimal effort levels of a risk-neutral agent with a bonus-malus contract write:

$$\begin{aligned}-c'(e_1^n) = p'(e_1^n)D + p'(e_1^n)\Big(&c(e_2^S) - c(e_2^{\overline{S}}) \\ &+ (p_0 - p(\overline{e}))(L-D) + (p(e_2^S) - p(e_2^{\overline{S}}))D\Big)\end{aligned} \tag{4.10}$$

$$-c'(e_2^{S^n}) = p'(e_2^{S^n})D \tag{4.11}$$

$$-c'(e_2^{\overline{S}^n}) = p'(e_2^{\overline{S}^n})D \tag{4.12}$$

For a risk-neutral agent with a bonus-malus contract, the optimal effort in the second period is independent of the loss occurrence during the previous period, as it appears from Eq. (4.11) and Eq. (4.12). Hence, we have:

$$-c'(e_2^n) = p'(e_2^n)D\,, \tag{4.13}$$

and we can rewrite Eq. (4.10) as follows:

$$-c'(e_1^n) = p'(e_1^n)\Big(D + (p_0 - p(\overline{e}))(L-D)\Big)\,. \tag{4.14}$$

From Eq. (4.14), we conclude that for a risk-neutral agent with a bonus-malus contract, the optimal effort levels in two periods are independent, as they are for the risk-neutral agent with a behavioral contract.

Proposition 4.1. *Consider a bonus-malus contract. The second-period prevention level of a risk-neutral agent or an agent with CARA preferences is independent of the loss occurrence in the previous period.*

[16]Result depends on the relationship between the optimal level of protection $p(e^*)$ and a critical probability p^c. The expression for critical probability being complex and depending on the exact shape of the measure of absolute risk aversion, we choose not to present it here.

This observation is due to the fact that both risk neutrality and CARA preferences neutralize the wealth effect. The loss occurrence implies an increase in premium level for the following period, and therefore a decrease in wealth. Yet, as we have mentioned above, the variations of wealth do not affect the optimal level of effort for a CARA agent nor a risk-neutral agent.

Comparison of the optimal effort levels for two contracts

Naturally, a risk-neutral agent provides the same effort in the second period regardless of the contract type, since prevention effort in the last period affects only the probability of a loss (Eq. (4.6) and Eq. (4.13)). In the first period (Eq. (4.5) and Eq. (4.14)), a risk-neutral agent provides a higher effort with a behavioral contract compared to a bonus-malus contract. The marginal benefit of prevention effort in case of the bonus-malus contract is smaller because of the distance between the two possible premium levels, $p_0 - p(\bar{e})$.

Proposition 4.2. *At the optimum, a risk-neutral agent provides a higher effort with a behavioral contract, compared to the bonus-malus contract, except for the last period when the optimal effort is the same regardless of the contract type.*

Considering risk-averse agents, we should first say that a risk-averse agent does not necessarily provide more effort than a risk-neutral agent, regardless of the contract type. For instance, in case of behavioral contract, we find that in second period a risk-averse agent invests more in self-protection than a risk-neutral agent if and only if the optimal investment of a risk-neutral agent is below a utility-dependent threshold $\hat{p}$,

$$\hat{p} = \left(\frac{u(B_2) - u(A_2)}{D} - u'(B_2) \right) \times \frac{1}{u'(A_2) - u'(B_2)} . \tag{4.15}$$

Interestingly, this threshold is similar to the one provided by Eeckhoudt, Gollier, and Schlesinger (2011), despite the fact that the authors model self-protection without insurance.[17]

In general, the optimal level of self-protection does not necessarily increase with risk-aversion, as it is confirmed by the main findings from the literature on risk prevention and self-protection, discussed in Section 4.2.1. Moreover, no risk-averse utility function satisfies a monotonic relationship between risk aversion and the level of self-protection (Briys and Schlesinger, 1990). Since an investment in self-protection adds the cost of self-protection to the potential loss, it deteriorates the

[17] The details of computations are provided in Appendix C.1.

worst possible state even further. Hence, an investment in self-protection produces a mean-preserving spread at lower wealth levels and increases the downside risk. As a consequence, risk-averse *and* prudent agents tend to invest less in self-protection. Besides, risk-seeking and prudent agents also tend to invest less in self-protection than non-prudent ones, for the same reason.[18]

This observation adds significant complexity to the comparison of risk-averse agents insured through different contracts. Moreover, the optimal level of prevention for a risk-averse agent with a bonus-malus contract might depend on the degree of absolute risk aversion, as we mentioned previously. Hence, we do not provide a theoretical proposition on the comparison of the optimal levels of prevention under different contracts for risk-averse agents. Nevertheless, we will elicit risk preferences in our experiment and provide some results on risk-averse and risk-seeking agents, thus testing our proposition on the higher levels of effort with a behavioral contract (Prop. 4.2) for different risk preferences.

As we mentioned previously, the optimal prevention effort and the link between risk attitudes and self-protection ultimately depend on multiple factors, regardless of the contract type. The determinants of the optimal prevention effort include the initial level of loss probability p_0, the effectiveness of prevention determined by the probability function $p(e)$, the individual characteristics such as risk aversion determined by the utility function $u(w)$, as well as the cost $c(e)$.

Given the multiplicity of factors affecting the optimal effort of prevention, we assume the functional forms for the cost function and the probability function, such that the standard properties used in our model are verified.[19] In particular, we make the following assumptions on prevention technology: $c(e) = be^2$, with b the cost parameter, and $p(e) = p_0 - ae^{0.5} > 0$, with a the parameter defining the effectiveness of self-protection technology in reducing loss probability, $a > 0\,, b > 0\,, p_0 > 0$.

In the following, we study the impact of initial loss probability and cost of prevention on the optimal prevention effort. For the behavioral contract, from the first order conditions (Eq. (4.3) and Eq. (4.4)), we obtain for a parameter α:

$$\frac{de_1}{d\alpha} = \frac{V_{e_1e_2}V_{e_2\alpha} - V_{e_1\alpha}V_{e_2e_2}}{V_{e_1e_1}V_{e_2e_2} - (V_{e_1e_2})^2} \tag{4.16}$$

$$\frac{de_2}{d\alpha} = \frac{V_{e_1e_2}V_{e_1\alpha} - V_{e_2\alpha}V_{e_1e_1}}{V_{e_1e_1}V_{e_2e_2} - (V_{e_1e_2})^2} \tag{4.17}$$

[18] Crainich, Eeckhoudt, and Trannoy (2013) and Jindapon (2013) provide some relevant findings on risk lovers, prudence, and self-protection.

[19] An increasing and convex cost function verifying $c'(e) > 0, c''(e) > 0$ and $c(0) = 0$, and a decreasing and convex loss probability function verifying $p'(e) < 0, p''(e) > 0$, and $p(0) = p_0$.

with a positive denominator $V_{e_1e_1}V_{e_2e_2} - (V_{e_1e_2})^2$ under A1.

We can show that both the impact of prevention cost and the impact of loss probability are ambiguous even when functional forms for both functions are specified. The details of derivations are provided in Appendix C.1.

The ambiguous impact of the cost of prevention on the optimal prevention effort can be explained by the following. An increase in the cost of prevention produces both a wealth effect and a substitution effect, similar to what is shown for the cost of insurance by Gollier (1994). The substitution effect is negative since an increase in the cost of prevention leads agents to invest less in self-protection. At the same time, the wealth effect is ambiguous in the case of self-protection, as we mentioned previously, because of the ambiguous impact of wealth variations for DARA and IARA agents. For instance, if all the parameters are such that an increase in risk-aversion produces a decreasing investment in self-protection, and simultaneously an increase in cost produces more risk-aversion, then an increase in cost would result in less self-protection. Otherwise, the conclusion would depend on the relative size of wealth effect and substitution effect: if the former is greater than the latter, an increase in cost might produce an increase in self-protection.

4.3.3 Theoretical predictions and experimental treatments

Based on the propositions and discussions provided in the previous subsections, we derive a set of hypotheses that we will test in our experiment.

Hypothesis H1. *The level of prevention effort is higher under the behavioral contract compared to the bonus-malus contract.*

Hypothesis H1 is based on Proposition 4.2. As we stated previously, we do not provide a theoretical result for the comparison of the optimal levels of prevention under different contracts for a risk-averse agent, but we will also test this hypothesis for all types of risk preferences and discuss the results that we observe in our experimental data.

Hypothesis H2. *Following the loss occurrence in period $t-1$, the level of effort in period t is unchanged for all the agents insured through the behavioral contract and for the risk-neutral agents and CARA agents insured through the bonus-malus contract.*

Hypothesis H2 is based on Proposition 4.1 regarding the bonus-malus contract. For the behavioral contract, this theoretical prediction stands by construction.

We will additionally test whether more prudent agents invest less in self-protection than less prudent ones. We will test this hypothesis for risk-averse agents and for risk-seeking agents, given the evidence provided by the literature.

Hypothesis H3. *The level of prevention effort decreases with the degree of prudence for risk-averse and risk-seeking agents.*

Choice of parameters for the experiment.

Given the ambiguous predictions regarding the cost and the initial loss probability, we consider four treatment conditions that would enable us to compare various possible combinations of both elements.[20] We use three different levels of initial loss probability, $p_0 = 0.2, 0.4$ and 0.6. While the loss probability of 0.4 and 0.6 is undoubtedly high, both levels are chosen to test a possible difference induced by a loss probability close to or higher than $1/2$.

For these three treatments, we set the cost of prevention effort at a low level ($b = 6.5$). We add a fourth treatment with a high cost of prevention effort ($b = 22$) and a high loss probability. The four treatments are summarized in Table 4.1. The range of possible levels of prevention effort is fixed to $e \in [0, 20]$, and the effectiveness of self-protection is fixed to $a = 0.14$.

Table 4.1: Experimental treatments

Treatment	Cost	Loss probability	p_0
T1	Low	Low	0.2
T2	Low	Intermediate	0.4
T3	Low	High	0.6
T4	High	High	0.6

We have also computed the optimal levels of effort under both contract types and the resulting utility, using a power function. The example of a power utility function shows that the choice of contract type might depend on the initial loss probability, the cost of effort, and the degree of risk aversion.

For instance, given the chosen function, the optimal choice of contract type regardless of the risk preference is a behavioral contract when the cost of prevention effort is low ($b = 6.5$) and the loss probability is high ($p_0 = 0.6$). An optimal choice is a bonus-malus contract when the loss probability is low ($p_0 = 0.2$), in otherwise similar conditions.[21] In other cases, the optimal choice depends on the degree of

[20] We also use an elicitation procedure to distinguish different types of absolute risk aversion, as will be explained in Section 4.4.

[21] We have used a power function $u(W) = w^r$, with $(1 - r)$ the degree of risk aversion, which implies DARA and prudence for risk-averse agents. The announced results hold for all $r \in [0, 1.5]$.

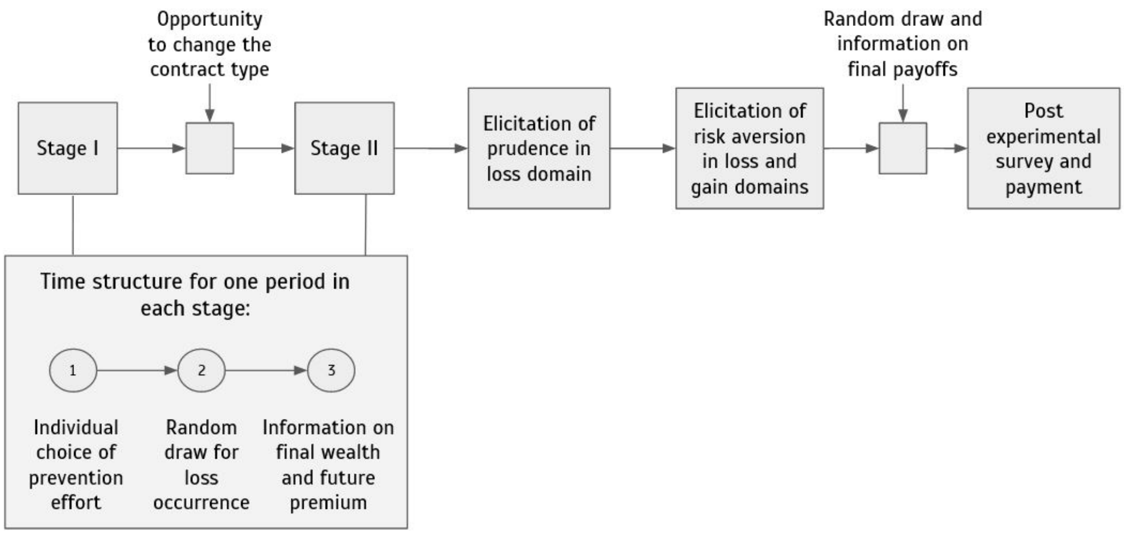
risk aversion.[22] With an exponential utility function representing CARA agents, the behavioral contract is almost always preferred to the bonus-malus contract.[23]

4.4 Experimental design

The main experiment consists of a repeated game in which each subject has to choose the desired level of prevention to avoid the occurrence of an accident (see subsection 4.4.1 below). In addition, we also elicit the subjects' level of prudence in the loss domain and the risk aversion both in the gain and the loss domains, as well as the degree of absolute risk aversion (subsection 4.4.2).

Subjects were told that the experiment consisted of successive parts, but the instructions for each part were made available and read out loud before each respective part.[24] The instructions were also distributed on paper to each subject. The timeline of the experiment is presented in Figure 4.1.

Figure 4.1: Timeline of the experiment



The experiment was computerized. Upon arrival, each subject was randomly assigned a computer. The instructions were read aloud by the experimenter and, before starting, a comprehension questionnaire was administered to check that the rules were well understood. All questions were answered in private.

[22]When the loss probability is 0.4, or the cost of prevention effort is high, most risk-averse DARA agents ($r \leq 0.7$) should optimally choose a behavioral contract, while risk-neutral and risk-seeking agents should choose a bonus-malus contract.

[23]For the utility function $u(W) = -e^{-rw}$, the behavioral contract provides a higher utility in all cases, except when $p_0 = 0.2$ and the agent is extremely risk-averse ($r < 0.03$). The optimal effort levels are otherwise close to the levels derived with a power function for DARA case.

[24]The instructions in French are provided in Appendix C.2.

4.4.1 Individual choice of prevention effort and contract type

Stage 1. The main experiment consists of two stages, with eight periods per stage. During the first stage, all the subjects are insured through the bonus-malus contract. At the beginning of each period, subjects receive an endowment of 500 ECU (Experimental Currency Unit) each. They are informed that the insurance is mandatory, so that they have to pay, in each period, the insurance premium based on their accident occurrence. Having an accident implies a loss of 300 ECU, but the mandatory insurance covers 200 ECU of this loss. Hence, the deductible of 100 ECU constitutes the effective loss in case of an accident. All this is made clear to the subjects to enforce the insurance context of the game.

In each period, the subjects can affect the probability of a loss by providing some prevention effort. Effort provision takes the form of monetary investment in prevention. That is, at the beginning of each period subjects can choose a level of prevention effort, ranging from 0 to 20. The higher the chosen level, the greater the loss probability reduction and the monetary cost of prevention.[25] To facilitate the subjects' decision, a simulator is shown on the screen, so that the subjects can see how the changes in the level of effort affect their loss probability.[26]

Once the level of effort is chosen, a random draw depending on the treatment condition determines if the subject has an accident or not, and the premium for the next period is calculated. A summary screen with the information on the total gain for the period, the premium paid and the premium for the next period is presented. The same task is repeated for eight periods.

Stage 2. Before starting the second stage of the game, subjects are offered the possibility to change their contract type for the next eight periods. The behavioral contract is presented, and the subjects can decide to either keep the bonus-malus contract or switch to the behavioral contract. Once they have made their choice, the second stage of the game begins, which is similar to Stage 1, except that the insurance premium is now calculated according to the type of insurance contract that has been chosen.

If the bonus-malus contract is chosen, the premium for the next period is calculated based on the accident occurrence resulting from the random draw at the end of the period, as previously explained. If the behavioral contract is chosen, the

[25]The function that transforms the level of effort into the loss probability is a nonlinear function, as previously described. The same holds true for the cost function.

[26]The screenshot of the simulator is provided with the instructions in Appendix C.2.

premium for the next period is calculated based on the effort level provided for the ongoing period. Namely, the premium is based on the effective loss probability resulting from the effort provision and is announced from the beginning of the period, when the effort level is chosen.

Once subjects have completed the two stages of the game, a summary screen provides an overview of the gains in each period played. Two periods are randomly chosen for payment but the subjects are informed of their gains for this part at the very end of the session.

4.4.2 Elicitation of prudence and risk aversion

After having played the main game, the subjects proceed with an elicitation part, consisting of two sub-stages: the elicitation of prudence in the loss domain and the elicitation of risk aversion in the gain and loss domains.

Prudence task in loss domain. We elicit prudence following Noussair et al. (2014) and Brunette and Jacob (2019). The subjects face five lottery choices framed in loss domain (Brunette and Jacob, 2019). The choice tasks are presented in Table 4.2, where $[x\_y]$ denotes a lottery with two possible outcomes, x and y. All lotteries are equiprobable with each outcome having 50% chance of occurrence. They are presented as compound lotteries. The visual representation uses dice of different colors to emphasize the independence of each risk.

Table 4.2: Choice tasks for prudence.

	Left lottery	Right lottery
Prudence 1	[-90_(-60+[20_-20])]	[(-90+[20_-20])_-60]
Prudence 2	[-90_(-60+[10_-10])]	[(-90+[10_-10])_-60]
Prudence 3	[-90_(-60+[40_-40])]	[(-90+[40_-40])_-60]
Prudence 4	[-135_(-90+[30_-30])]	[(-135+[30_-30])_-90]
Prudence 5	[-65_(-35+[20_-20])]	[(-65+[20_-20])_-35]

In all the left lotteries, the additional zero-mean risk is attached to the "good" state of nature (the one where the loss is smaller), while in all the right lotteries it is associated with the "bad" state. Hence, in a manner consistent with Eeckhoudt and Schlesinger (2006), the number of left lotteries chosen by the subject reflects the degree of prudence.

For this elicitation procedure, the subjects were endowed with 165 ECU to cover their maximum probable loss. The rate of conversion for this task was 1 euro = 25 ECU. At the end of the experiment, one of five decisions was randomly chosen.

Then the subjects had to proceed with the virtual throw of dice to determine their payoff for this stage.

Risk aversion. We elicit risk aversion with a paired-gamble method proposed by Drichoutis and Lusk (2016). As shown by Csermely and Rabas (2016), this version of the multiple-price list outperforms other methods, including the most used method proposed by Holt and Laury (2002). The latter method uses changing probabilities with fixed outcomes, while the version of Drichoutis and Lusk (2016) uses changing outcomes with fixed probabilities[27].

We adapt the method proposed by Drichoutis and Lusk (2016) to the loss domain, as presented in Table 4.3. We also alter the outcomes to maintain the switch point for the risk-neutral subjects at line 5. The probabilities are fixed to 0.5 for all cases, and only the highest possible loss varies. The difference in expected outcomes and the closed interval for the CARA coefficient were not presented to the subjects. For this elicitation procedure, all outcome values were presented directly in euros.

Table 4.3: Multiple-price list in loss domain

Lottery A		Lottery B		EV difference	Closed interval†	
-2.4	-1.60	-4.90	-0.75	0.825	$-\infty$	-0.46
-2.32	-1.60	-4.50	-0.75	0.665	-0.45	-0.44
-2.24	-1.60	-3.54	-0.75	0.225	-0.43	-0.25
-2.16	-1.60	-3.14	-0.75	0.065	-0.24	-0.1
-2.08	-1.60	-2.86	-0.75	-0.035	-0.09	0.06
-2.00	-1.60	-2.65	-0.75	-0.100	0.07	0.23
-1.92	-1.60	-2.48	-0.75	-0.145	0.24	0.4
-1.84	-1.60	-2.32	-0.75	-0.185	0.41	0.64
-1.76	-1.60	-2.17	-0.75	-0.220	0.65	0.94
-1.68	-1.60	-2.01	-0.75	-0.260	0.95	$+\infty$

†if subject switches to Lottery B, assuming EUT and CARA

For this first choice list, subjects were endowed with 5 euros. Once the choice was made, subjects were offered two options: either to keep this list or to give it up and make their choice again with a higher endowment (10 euros). Following Holt and Laury (2002), this was done to make subjects aware of the increase in wealth. The second option being dominant, we expected the majority of subjects to make their choice again with a higher endowment. The comparison between the switch point in the first and the second lists is used to elicit the type of absolute risk aversion. The

[27] The authors argue that the methods with changing probabilities are better suited to elicit the probability-weighting function, while the methods with changing outcomes provide a better elicitation of the curvature of the utility function.

subjects that switch at the same line in the second list are considered CARA, while those who switch earlier (later) than in the first list are considered DARA (IARA).

Finally, the unaltered version of the list in gain domain proposed by Drichoutis and Lusk (2016) was played by subjects, and one of two lists was chosen randomly for the payment.[28] Then, one line of the chosen list was randomly drawn, and the subjects had to proceed to the draw of a colored ball from a virtual urn to determine their payoff for this procedure.

4.4.3 Monetary incentives

The payoffs for the main game and the prudence elicitation part were presented in ECU (Experimental Currency Unit) with the conversion rules 75 ECU = 1 euro for the main part and 25 ECU = 1 euro for the prudence elicitation task. The conversion rules were announced in the instructions and on the screen for each part. The payoffs for the risk aversion elicitation task were presented in euros. Once the successive parts were completed, the screens displayed the total cumulative gains for the experiment. At the end of the session, subjects were paid their earnings in private. Average earnings were 19 euros (standard deviation = 3.67).

4.5 Results

A total of 196 subjects participated in eight sessions, with two sessions per treatment, in September 2020. All of the subjects were recruited from a list of experimental subjects maintained at BETA, University of Strasbourg, France, using ORSEE software. The experiment was conducted in French. Each session lasted an average of 75 minutes. Subjects were on average 22 years of age, and 50% of the subjects were female. They were involved in a wide range of fields, and 27.5% of them were studying economics or business management.

In order to assess the difference between the four treatment conditions both in terms of their effect on the level of prevention effort and the choice of contract in Stage 2, we present our results in three steps.

First, we explore the results on how the effort level varies in the first part of the game, where all the subjects in all treatments were assigned a bonus-malus contract. Then we investigate the level of effort provided in the second part, given that the subjects have chosen their insurance contract in between two parts of the game.

[28] If the subject kept the first list, either the first or the third list in the gain domain was randomly chosen for payment. If the subject gave up the first list, either the second or the third list in the gain domain was randomly chosen for payment.

Second, we look at the effect of treatments on the choice of contract. In particular, we relate the effort made in the first eight periods with that choice and identify possible self-selection behavior. We re-examine the first eight periods of our experiment and analyze our findings by comparing both parts of the game.

Finally, we proceed with some relevant econometric regressions to verify our results and to obtain more insights on the determinants of both the effort level and the contract choice. We aim at deepening our insights in two ways. First, we want to determine whether the effort provided in the second part of the game and the choice of the contract are related to the personal experience in the first part. And more importantly, we want to determine the role of the individual characteristics that could explain the choice and the effort level both in the first and the second part of the game.

4.5.1 Average prevention effort in the first and second parts of the game

In the first eight periods of the game (Part 1), all subjects were assigned a bonus-malus contract (BM). Table 4.4 summarizes the average effort in each treatment in Part 1 and Part 2 given the contract played (columns (1) and (2)).

Table 4.4: Average effort (per treatment and per contract played)

	(1)	(2)		(3)	
Treatment	Part 1	Part 2		Part 1 given Part 2†	
	BM	BM	BC	BM	BC
T1	11.305	9.924	13.897	9.928	13.978
	(6.126)	(5.877)	(6.645)	(5.288)	(6.747)
T2	11.247	6.885	13.275	7.667	12.475
	(5.289)	(4.277)	(5.422)	(4.952)	(4.823)
T3	12.589	10.607	14.295	10.232	12.982
	(5.856)	(8.017)	(4.999)	(7.035)	(5.551)
T4	9.922	8.200	9.541	9.450	10.041
	(5.439)	(5.606)	(5.660)	(5.066)	(5.529)

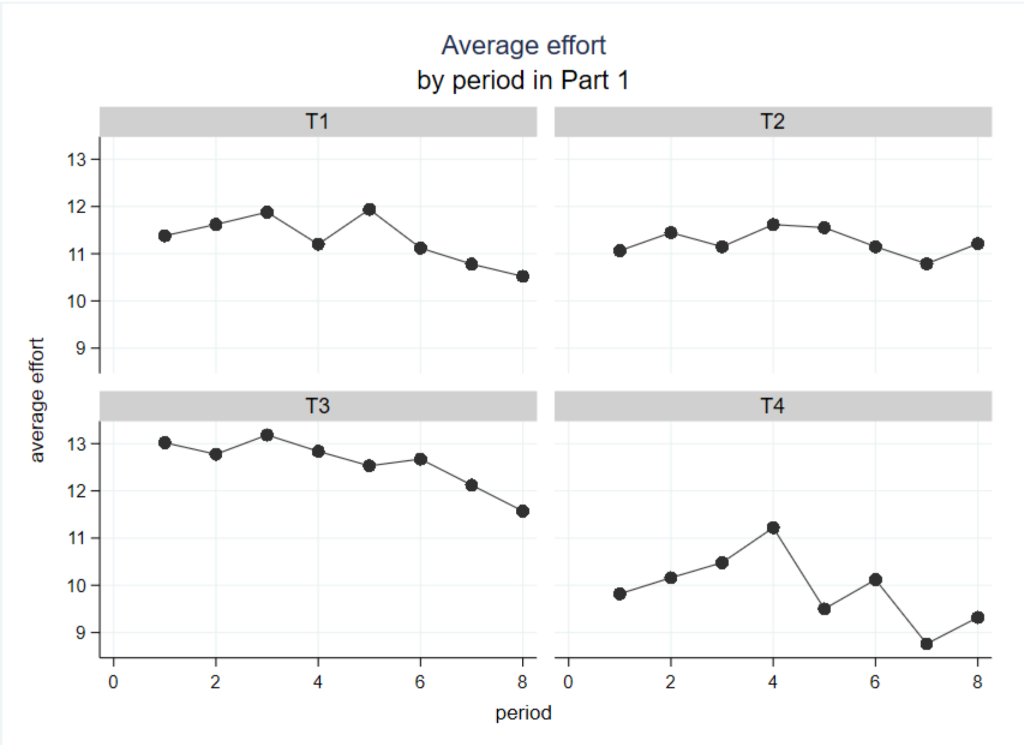
Standard deviation in parentheses

†Given the contract played in Part 2, or the *choice* of contract

During the first eight periods, the average levels of effort are not very different between treatments. Tests of significant difference using two-sided Mann-Whitney rank-sum test and taking subjects' averages as the unit of observation are reported in Table C.1 in the Appendix. We find no difference in average between the levels of effort provided in different treatments, except between T3 and T4 ($z = 3.272$, p-value $= 0.0011$), which differ by the cost of prevention effort.[29]

Figure 4.2 illustrates the average effort per period in Part 1 and shows the same results when comparing the treatments. The level of effort is similar in T1, T2, and T3 along periods and is much lower in T4. At this point, it seems that only the cost of prevention affects the effort level, while the initial loss probability produces no impact.

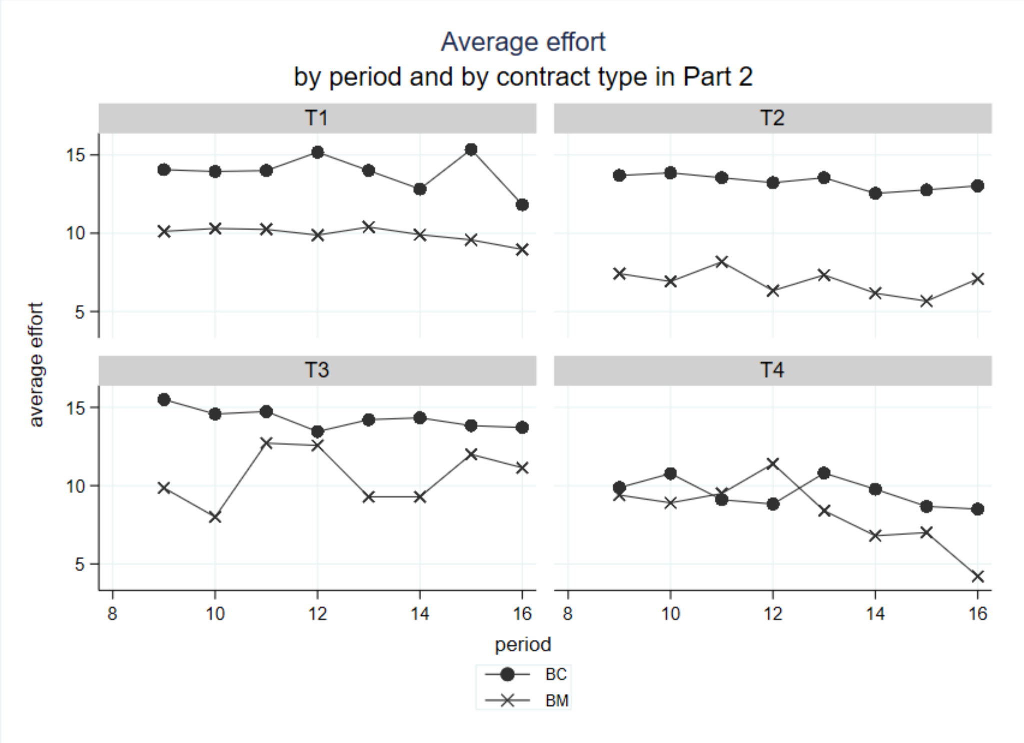
Figure 4.2: Average effort in Part 1 (per treatment)



Considering the average levels of effort in Part 2 according to the chosen contract type (illustrated by Figure 4.3), we observe no significant difference between treatments for the subjects with a BM contract, except, somewhat surprisingly, between the first two treatments, T1 and T2 (p-value $= 0.0451$). When we look at the subjects that have chosen the BC contract instead, the difference in average efforts is significant between T4 and all other treatments (p-value < 0.01, see Table C.2 in the Appendix). This seems to support the results observed for the first part of the game, namely that the cost of prevention has more impact on the level of effort than the loss probability, at least in the case of the behavioral contract.

[29] In those treatments the loss probability is 0.6, but the cost is higher in T4.

Figure 4.3: Average effort in Part 2 (per treatment and contract type)



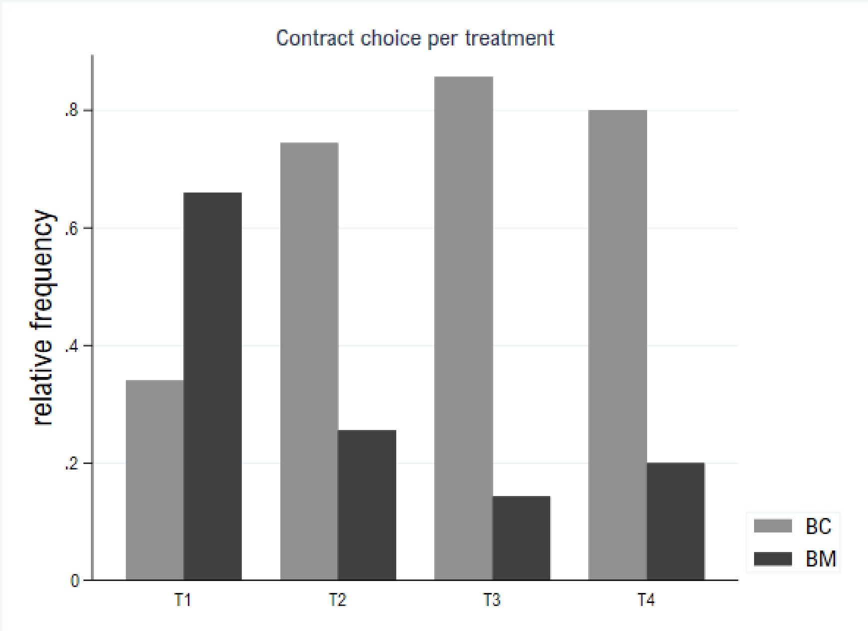
When we compare the average efforts per treatment in Part 2 *between contract types*, we observe that the subjects insured through a BC contract provide higher levels of prevention effort than those insured through a BM contract. However, the difference between BM and BC is only highly significant for treatments T1 (z = -2.470, p-value = 0.0135) and T2 (z = -3.822, p-value = 0.0001) but not for T3 and T4. It appears that subjects exert more prevention effort under the BC contract compared to the BM contract when the initial loss probability is below 0.5 (either 0.2 or 0.4).

4.5.2 Choosing a contract

One important aspect of Part 2 is that the subjects had the possibility to choose the insurance contract. Before starting the last eight periods of the game, subjects were offered a possibility to choose between a BM contract and a BC contract. Figure 4.4 presents the distribution of contract choices per treatment. In all treatments except T1, a vast majority of subjects prefer the BC contract and this proportion appears to increase with the level of the probability of a loss. In T4, the increase of the cost of prevention does not seem to add an effect to the increase of probability in T3.

This result can be explained by the fact that the premium in case of a BM contract is fully determined by the accident occurrence in the previous period, making

Figure 4.4: Contract choice (per treatment)



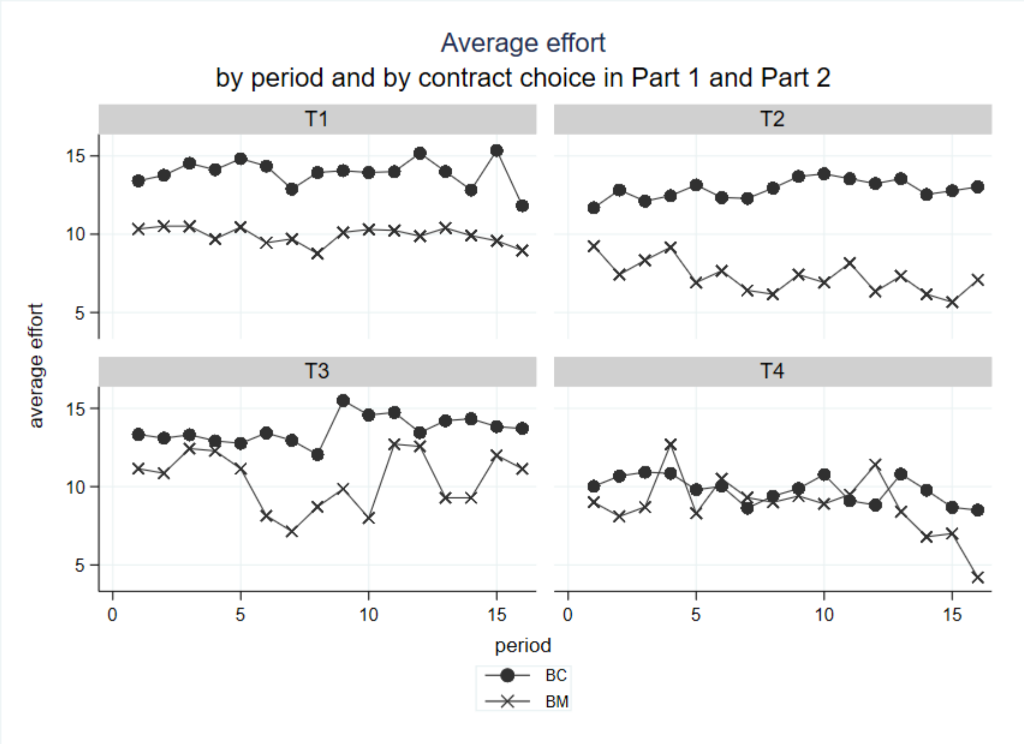
it less advantageous to keep this contract when the accident probability is high.

At this point, we must consider the fact that the choice of contract also reflects the willingness to provide the prevention effort. Saying differently, we may have self-selection into an insurance contract that reflects individual preferences for risk and/or prevention. These individual characteristics that do not change during the game may also explain that the effort provided in the second part of the game is actually related to the effort level in the first part, even if the contracts are different.

Figure 4.5 shows the average effort per period for the two parts but making a difference according to the choice made in Part 2: those who choose BC and those who keep BM. It appears that the subjects who, on average, provide less effort when insured through the BM contract, decide to keep this contract afterward. On the contrary, those who choose the BC contract are already high effort providers in the first periods.

Those results can be seen in Table 4.4 as well, by comparing the average effort levels in Part 2 to the average levels in Part 1, given the contract choice (columns (2) and (3)). We report the results of the Mann-Whitney rank-sum test of the difference between the averages in Table C.3 in the Appendix. We find no significant difference between the levels of effort in Part 1 compared to Part 2 according to the contract choice, meaning that the same subjects have provided a statistically similar level of effort in the first and the second parts, independently of their choice of contract. It seems that the subjects choose the contract type according to the level of effort they provide from the start, which suggests that the choice of the contract is determined

Figure 4.5: Average effort per period (per treatment and contract choice)



by the individual preferences for prevention and personal characteristics.

This evidence is also supported by the fact that the differences between treatments observed in the second part of the game were already present in the first part. For instance, the difference between contract types observed for treatments T1 and T2 is also significant in Part 1, as it is shown in Table C.3 in the Appendix.

A similar observation emerges from the comparison of differences in the average effort levels *between treatments* given the contract type: the differences observed in the second part of the game are present in the first, even if slightly less significant (Table C.4 in the Appendix). Besides, the difference between treatments T3 and T4, discussed at the beginning of this section in relation to the first part of the game, is effectively observed only for the subjects that have chosen BC in the second part.

The results suggest that the difference between treatments in terms of effort provision is persistent through the entire game and that the contract choice is determined by the preferences for prevention showing up well before the choice. Consequently, it is important to explore the determinants of the prevention effort such as age, gender, risk aversion, or prudence. Thus, we perform an econometric analysis of the determinants of effort provision as well as contract choice.

4.5.3 Econometric analysis

We further perform a series of econometric regressions to verify the validity of our observations resulting from the non-parametric analysis and to obtain insights on the determinants of the effort level and the choice of contract. In what follows, we aim to explore the extent to which the effort level and the contract choice are influenced by the treatment conditions, but more importantly by the individual characteristics and the individual experience throughout the game. This would allow us to test our hypotheses and to shed some light on the underlying motives to exert prevention effort and on the potential incentives for self-protection that behavioral contract could, or could not, provide.

The first two columns in Table 4.5 present Tobit estimations of the determinants of effort provision.[30] The dependent variable is the individual prevention effort per period. Each specification includes control for age and gender. In addition to the treatment variables, we also introduce a period variable and control for having experienced a loss in the past period. The reference is *T1*.

The first column is related to Part 1 only, namely to the first eight periods. The regression results confirm our findings discussed in the previous section on non-parametric analysis. There is no difference between T1 and the other treatments. If we test for differences between coefficients, we find a significant difference between T3 and T4 (Wald test: F=11.46, p-value = 0.0007). Subjects who were assigned to the treatment group T4 (high loss probability and high prevention cost) made less effort on average, other things being equal, in the first part of the game than those who were assigned to the treatment group T3 (high loss probability and low prevention cost).

The accident occurred during the previous period (controlled through the variable "Loss in t-1") has a negative impact on the effort level in the first part of the game. We also observe that the effort is decreasing with the advancement in the experiment (controlled through the "Period" variable), suggesting a possible effort adjustment related to the experience.

Risk aversion and prudence are relevant in explaining the effort level in this first part. We use the number of safe choices in the multiple-price list task in the loss domain as a measure of risk aversion in losses, and the number of prudent choices (0 to 5) as a measure of the degree of prudence. Subjects are considered risk-seeking if they switch to the more risky lottery before the fifth line.[31] We find that risk-

[30]We present results using a Tobit regression model with standard errors clustered at the individual level. However, all the results are robust to the use of other specifications such as OLS, panel random-effect model, or session clustered and treatment clustered standard errors.

[31]Given that a risk-neutral subject should switch at line five, and that it was impossible to

seeking subjects have made less effort than risk-neutral and risk-averse subjects. Moreover, we find that more prudent subjects made less effort in the first part, which is consistent with our hypothesis H3 at this point.

Table 4.5: Regression results for the determinants of the effort level and the contract choice

	(1) Part 1	(2) Part 2	(3) Choice
T2	0.0354	-0.812	0.261***
	(1.189)	(0.997)	(0.0779)
T3	1.809	-0.519	0.301***
	(1.195)	(1.145)	(0.0996)
T4	-1.369	-3.152***	0.286***
	(1.097)	(1.150)	(0.0999)
Risk seeking (in losses)	-2.977**	-0.0806	0.0355
	(1.204)	(0.914)	(0.102)
Prudence	-0.539*	-0.578**	0.00404
	(0.324)	(0.239)	(0.0230)
Age	0.0804	0.0454	0.0133
	(0.0814)	(0.106)	(0.00902)
Women	-1.379*	-0.0143	0.0188
	(0.772)	(0.583)	(0.0570)
Period	-0.205***	-0.218***	
	(0.0765)	(0.0761)	
Loss in t-1	-0.982**	-0.626	
	(0.464)	(0.399)	
Contract played (BC)		1.543**	
		(0.750)	
Number of losses in Part 1		0.440*	0.0381
		(0.234)	(0.0236)
Average effort in Part 1		0.947***	0.0277***
		(0.0781)	(0.00600)
Constant	16.08***	7.048**	
	(2.550)	(3.389)	
Observations	1,372	1,372	196

Robust standard errors in parentheses
*** $p<0.01$, ** $p<0.05$, * $p<0.1$

In the second column of Table 4.5, the results from a similar regression are presented, except that we also control for the contract chosen and played effectively

make non-consistent choices in this task, subjects are considered risk-seeking if the number of safe choices they made is less than five.

("Contract Played (BC)"). We also introduce the controls for the number of losses made in Part 1, as well as the average effort that subjects had provided during Part 1. This is because our descriptive results above have shown that there seems to be a continuity of effort provision in two successive parts. Besides, if subjects have revealed some preferences for prevention in Part 1 (risk-seeking, prudence), we also control for them in this regression.

We find that the subjects with a behavioral contract made significantly more effort. This result supports our hypothesis H1 and it is significant despite the fact that we also control for the average effort level provided during Part 1. This might suggest that behavioral contract provide some incentives for prevention despite the fact that the effort level is mainly determined by the individual preferences already present in Part 1. Further analysis of the possible interaction between these variables is needed to conclude on the prevention incentives provided by a behavioral contract.

Result 4.1. *The level of prevention effort is higher under the behavioral contract compared to the bonus-malus contract (H1).*

Interestingly, the accident occurred during the previous period, which has a negative impact on the effort level in the first part of the game, does not seem to have any significant impact in the second part. This could be due to the fact that most of the subjects have chosen the behavioral contract for the second part (Figure 4.4), except for the first treatment, where the loss probability was very low. This partially confirms our hypothesis H2, but further analysis is needed in order to provide a definitive conclusion.

Result 4.2. *Following the loss occurrence in period $t-1$, the level of effort in period t is not affected for the agents insured through the behavioral contract (H2).*

We also observe that T4 is indeed the only treatment that significantly affects the level of effort, considering the general level of effort provided during the experiment and controlling for the contract played.[32] This supports our observation resulting from the non-parametric analysis, which suggests that the cost of prevention affects the level of effort, while the initial loss probability does not. This observation is also supported by the fact that the difference between treatments T3 and T4 is more prominent than between T4 and two other treatments.

We also see that prudence remains a significant determinant of the effort level in the second part, as it was in the first, which confirms our hypothesis H3. Yet, the risk seeking does not seem to affect the level of preventive effort anymore.

[32] Wald test comparing the parameters for treatment T2 and T4: F=6.31, p-value=0.0120. Wald test comparing the parameters for treatment T3 and T4: F=20.86, p-value=0.0000.

Result 4.3. *The level of prevention effort decreases with the degree of prudence (H3).*

The third column of Table 4.5 presents Probit estimations of the determinants of contract choice. We present the marginal effects of these estimations. The dependent variable is the choice of behavioral contract. We find that the treatments appear to be an important determinant of the choice of behavioral contract. The subjects assigned to the treatments T2, T3, and T4 were more likely to choose the behavioral contract than the subjects assigned to the treatment T1 (26%, 30%, and 29% more chances respectively).

Apart from the treatment effects, it appears that the only significant determinant of contract choice is the average effort provided during the first part of the game. This result implies that the subjects who provided a higher effort level during the first part of the game were more likely to choose the behavioral contract for the second part. Interestingly, the experience did not seem to have an impact on the contract choice: the number of accidents during the first part of the game does not affect significantly the probability to choose the behavioral contract.

4.6 Conclusion

In the present chapter, we explore how the contract type affects the policyholders' preventive actions, namely the effort provided to reduce the probability of an accident. We also analyze the potential determinants of contract choice, when bonus-malus and behavioral contracts are offered.

We find that the subjects choosing a behavioral contract provide higher levels of prevention effort than the subjects choosing a bonus-malus contract. There also seems to be self-selection according to the individual preferences for prevention: the subjects who provide a higher level of effort in the first part of the experiment, choose to continue with a behavioral contract, while those who provide low effort prefer to keep a bonus-malus contract. Nevertheless, we find that the choice of contract type is a significant determinant of the provision of prevention, even if we control for the average level of effort provided during the first part of the experiment.

Considering the impact of an accident, our findings are not clear. The loss occurrence is a significant determinant of the effort in the first part of the game, but less so in the second part. Besides, our results also confirm the theoretical findings that the prevention effort depends on risk aversion and prudence. In particular, we find that risk-seeking individuals provide less effort to decrease their loss probability, and the same holds true for more prudent subjects.

Appendix C

C.1 Optimal prevention level

FOC for the risk-averse agent with a behavioral contract

We can rewrite the expression of the expected utility of a risk-averse agent,

$$V(e_1, e_2) = Eu(e_1) + \delta Eu(e_1, e_2),$$

with δ equal to 1, as follows:

$$V(e_1, e_2) = p(e_1)u(A_1) + (1 - p(e_1))u(B_1) + p(e_2)u(A_2) + (1 - (p(e_2))u(B_2).$$

Then, the first-order condition for the optimal effort level e_1^* writes:

$$\begin{aligned}
\frac{\partial V(e_1, e_2)}{\partial e_1} &= p'(e_1)u(A_1) + p(e_1)u'(A_1)\frac{dA_1}{de_1} \\
&+ u'(B_1)\frac{dB_1}{de_1} - p'(e_1)u(B_1) - p(e_1)u'(B_1)\frac{dB_1}{de_1} \\
&+ p(e_2)u'(A_2)\frac{dA_2}{de_1} \\
&+ u'(B_2)\frac{dB_2}{de_1} - p(e_2)u'(B_2)\frac{dB_2}{de_1} = 0
\end{aligned}$$

Given that $\frac{dA_t}{de_t} = -c'(e_t)$, we have:

$$\begin{aligned}\frac{\partial V(e_1,e_2)}{\partial e_1} &= p'(e_1)u(A_1) - p(e_1)u'(A_1)c'(e_1)\\ &- u'(B_1)c'(e_1) - p'(e_1)u(B_1) + p(e_1)u'(B_1)c'(e_1)\\ &- p'(e_1)(L-D)p(e_2)u'(A_2)\\ &- p'(e_1)(L-D)u'(B_2)\\ &+ p'(e_1)(L-D)p(e_2)u'(B_2) = 0\end{aligned}$$

Thus, we have the following condition for e_1^*:

$$\begin{aligned}&-c'(e_1^*)\Big(p(e_1^*)u'(A_1) + (1-p(e_1^*))u'(B_1)\Big) =\\ &\qquad p'(e_1^*)\Big(u(B_1) - u(A_1)\Big) + p'(e_1^*)(L-D)\Big(p(e_2)u'(A_2) + (1-p(e_2))u'(B_2)\Big)\,.\end{aligned}$$

For the second period, we obtain the following first-order condition:

$$\begin{aligned}\frac{\partial V(e_1,e_2)}{\partial e_2} &= p'(e_2)u(A_2) - p(e_2)u'(A_2)c'(e_2)\\ &- u'(B_2)c'(e_2) - p'(e_2)u(B_2) + p(e_2)u'(B_2)c'(e_2) = 0\end{aligned}$$

Thus, we have have the following condition for e_2^*:

$$\begin{aligned}-c'(e_2)\Big(p(e_2)u'(A_2) + (1-p(e_2))u'(B_2)\Big) &=\\ &p'(e_2)\Big(u(B_2) - u(A_2)\Big)\end{aligned}$$

FOC for the risk-averse agent with a bonus-malus contract

From the expected utility expression,

$$\begin{aligned}V(e_1, e_2^S, e_2^{\overline{S}}) &= p(e_1)u(A_1) + (1-p(e_1))u(B_1)\\ &+ p(e_1)\Big(p(e_2^S)u(A_2^S)) + (1-p(e_2^S))u(B_2^S)\Big)\\ &+ (1-p(e_1))\Big(p(e_2^{\overline{S}})u(A_2^{\overline{S}}) + (1-p(e_2^{\overline{S}}))u(B_2^{\overline{S}})\Big)\,,\end{aligned}$$

and given that $\frac{du(A_1)}{de_1} = -u'(A_1)c'(e_1)$, we have:

$$
\begin{aligned}
\frac{\partial V(e_1, e_2^S, e_2^{\overline{S}})}{\partial e_1} &= p'(e_1)u(A_1) - p(e_1)u'(A_1)c'(e_1) - u'(B_1)c'(e_1) \\
&- p'(e_1)u(B_1) + p(e_1)u'(B_1)c'(e_1) + p'(e_1)p(e_2)u(A_2^S) + p'(e_1)u(B_2^S) \\
&- p'(e_1)p(e_2^S)u(B_2^S) - p'(e_1)p(e_2^{\overline{S}}) - p'(e_1)u(B_2^{\overline{S}}) + p'(e_1)p(e_2^{\overline{S}})u(B_2^{\overline{S}}) \\
&= -c'(e_1)\Big(p(e_1)u'(A_1) + (1-p(e_1))u'(B_1)\Big) \\
&- p'(e_1)\Big(u(B_1) - u(A_1) - p(e_2^S)u(A_2^S) - (1-p(e_2^S))u(B_2^S) \\
&+ p(e_2^{\overline{S}})u(A_2^{\overline{S}}) + (1-p(e_2^{\overline{S}})u(B_2^{\overline{S}})\Big) \\
&= -c'(e_1)\Big(p(e_1)u'(A_1) + (1-p(e_1))u'(B_1)\Big) \\
&- p'(e_1)\Big(u(B_1) - u(A_1)\Big) - p'(e_1)\Big(Eu(e_2^{\overline{S}}) - Eu(e_2^S)\Big)
\end{aligned}
$$

Thus, we have the following condition for e_1^*:

$$
\begin{aligned}
-c'(e_1)\Big(p(e_1)u'(A_1)+(1-p(e_1))u'(B_1)\Big) = \\
- p'(e_1)\Big(u(B_1) - u(A_1)\Big) - p'(e_1)\Big(Eu(e_2^{\overline{S}}) - Eu(e_2^S)\Big) .
\end{aligned}
$$

For the second period, we have:

$$
\begin{aligned}
\frac{\partial V(e_1, e_2^S, e_2^{\overline{S}})}{\partial e_2^S} &= p(e_1)p'(e_2)u(A_2^S) - p(e_1)p(e_2^S)u'(A_2^S)c'(e_2^S) - p(e_1)u'(B_2^S)c'(e_2^S) \\
&- p(e_1)p'(e_2^S)u(B_2^S) + p(e_1)p(e_2^S)u'(B_2^S)c'(e_2^S) ,
\end{aligned}
$$

and thus,

$$
-c'(e_2^S)\Big(p(e_2^S)u'(A_2^S) + (1-p(e_2^S))u'(B_2^S)\Big) = p'(e_2^S)\Big(u(B_2^S) - u(A_2^S)\Big) ,
$$

and it can be computed in the same manner for $e_2^{\overline{S}}$.

Utility-dependent threshold $\hat{p}$ in case of behavioral contract

A risk-averse agent invests more in self-protection than a risk-neutral agent, $e_2^* > e_2^n$ iif:

$$
-c'(e_2^n)\Big(p(e_2^n)u'(A_2) + (1-p(e_2^n))u'(B_2)\Big) - p'(e_2^n)\Big(u(B_2) - u(A_2)\Big) > 0 ,
$$

which can be rewritten as:

$$p'(e_2^n)D\Big(p(e_2^n)u'(A_2) + (1 - p(e_2^n)u'(B_2)\Big) - p'(e_2^n)\Big(u(B_2) - u(A_2)\Big) > 0\,,$$

and since $p'(e) < 0$, we have:

$$D\Big(p(e_2^n)u'(A_2) + (1 - p(e_2^n)u'(B_2)\Big) - \Big(u(B_2) - u(A_2)\Big) < 0\,.$$

It follows that $e_2^* > e_2^n$ iif:

$$p(e_2^n) < \Big(\frac{u(B_2) - u(A_2)}{D} - u'(B_2)\Big) \times \frac{1}{u'(A_2) - u'(B_2)}\,.$$

Given that $A_2 < B_2\,, u(A_2) < u(B_2)$ and $u'(A_2) > u'(B_2)$ for a risk-averse agent. Consequently, the utility dependent threshold $\hat{p}$ exists such that $e_2^* > e_2^n$ if $p(e_2^n) < \hat{p}$, with $\hat{p}$ such that

$$\hat{p} = \Big(\frac{u(B_2) - u(A_2)}{D} - u'(B_2)\Big) \times \frac{1}{u'(A_2) - u'(B_2)}\,.$$

Comparative statics

Notice that A_t, B_t and $p(e_t)$ are functions of $f(p_0)$. We have:

$$\begin{aligned} V_{e_2p_0} = &\Big(-c'(e_2) - p'(e_2)(L-D)\Big)\Big(u'(A_2) - u'(B_2)\Big) \\ &+ c'(e_2)(L-D)\Big(p(e_2)u''(A_2) + (1 - p(e_2))u''(B_2)\Big) \end{aligned}$$

The overall sign of $V_{e_2p_0}$ is ambiguous. Notice that the second term is negative. Hence, the impact of loss probability on the optimal effort in second period is negative if $\Big(-c'(e_2) - p'(e_2)(L-D)\Big)\Big(u'(A_2) - u'(B_2)\Big)$ is negative, which is the case if $(-c'(e_2) - p'(e_2)(L-D))$ is negative. For the first period, we have:

$$\begin{aligned} V_{e_1p_0} = &\Big(-c'(e_1) - p'(e_1)(L-D)\Big)\Big(u'(A_1) - u'(B_1)\Big) \\ &+ c'(e_1)(L-D)\Big(p(e_1)u''(A_1) + (1 - p(e_1))u''(B_1)\Big) \\ &- p'(e_1)(L-D)\Big(u'(A_1) - u'(B_1) - (L-D)(u''(A_2) + (1 - p(e_2))u''(B_2))\Big) \end{aligned}$$

Here, the second term is negative, while the last term is positive, and the overall sign is ambiguous as well.

For the impact of cost on the optimal effort level, we have the following expressions for two periods:

$$
\begin{aligned}
V_{e_2 b} = -2e_2\Big(p(e_2)u'(A_2) + (1-p(e_2))u'(B_2)\Big) \\
+ 2be_2^3\Big(p(e_2)u''(A_2) + (1-p(e_2))u''(B_2)\Big) + p'(e_2)e_2^2\Big(u'(B_2) - u'(A_2)\Big)
\end{aligned}
$$

$$
\begin{aligned}
V_{e_1 b} &= -2e_1\Big(p(e_1)u'(A_1) \\
&+ (1-p(e_1))u'(B_1)\Big) \\
&+ 2be_1^3\Big(p(e_1)u''(A_1) + (1-p(e_1))u''(B_1)\Big) \\
&+ p'(e_1)e_1^2\Big(u'(B_1) - u'(A_1)\Big) + p'(e_1)(L-D)e_2^2\Big(p(e_2)u''(A_2) + (1-p(e_2))u''(B_2)\Big)
\end{aligned}
$$

The overall sign is also ambiguous, since the first two parts of each equation are negative, while the remaining parts are positive.

C.2 Experimental instructions in French

The instructions in French for the treatment T1 (loss probability of 0.2) are presented below.

Instructions

"Nous vous remercions de participer à cette expérience sur la prise de décision. Dans cette expérience, vous avez la possibilité de gagner de l'argent. Le montant de vos gains dépendra de vos décisions. Nous vous demandons donc de lire attentivement ces instructions, elles doivent vous permettre de bien comprendre l'expérience. Toutes vos décisions sont anonymes. Vous n'entrerez jamais votre nom sur l'ordinateur. Vous indiquerez vos choix à l'ordinateur devant lequel vous êtes assis. A partir de maintenant, vous n'êtes donc plus autorisés à communiquer avec les autres participants. Nous vous prions également d'éteindre vos téléphones portables. Si vous avez une question levez la main et un expérimentateur viendra vous répondre en privé. Cette expérience comprend 4 parties. Vous recevrez les instructions spécifiques à chaque partie avant de la commencer, et une fois la partie précédente terminée. Les instructions sont les mêmes pour tous les participants. Certains gains que vous pouvez accumuler en participant à cette expérience sont exprimés en ECU (unités monétaires expérimentales). Si les gains pour une partie du jeu sont exprimés en ECU, le taux de conversion vous sera donné avec les instructions. A la fin de l'expérience, tous vos gains seront convertis en euros selon le taux de conversion correspondant. Le total des gains que vous aurez réalisés vous sera payé en espèces à la fin de l'expérience, de façon privée."

Part 1

"Pour cette partie, le taux de conversion qui s'applique est de **1€= 75 ECU**. Cette première partie de l'expérience est composée de **8 périodes**. Au début de chaque période, vous recevrez 500 ECU qui constitueront votre dotation initiale pour la période. A chaque période, un dommage entraînant une perte de 300 ECU peut survenir aléatoirement avec une probabilité de **20%**. C'est-à-dire qu'il y a une chance sur cinq que le dommage entraînant une perte monétaire survienne. Vous devez obligatoirement vous assurer contre le risque de subir un dommage. Le contrat d'assurance a un prix appelé une prime d'assurance. Le principe du calcul de la prime d'assurance pour votre contrat vous sera détaillé plus bas. Cependant ce contrat d'assurance ne couvrira pas l'ensemble de la perte. En effet, le contrat auquel vous devez souscrire prévoit que 100 ECU restent à votre charge. C'est-à-dire, si le dommage de 300 ECU survient, l'assurance vous indemnise 200 ECU, et 100 ECU resteront à votre charge. Ainsi, vous perdrez 100 ECU de votre dotation initiale.

L'effort de prévention et la probabilité d'un dommage. Vous avez la possibilité de réduire la probabilité qu'un dommage survienne en choisissant de fournir un effort de prévention. Plus précisément, au début de chaque période, vous devez décider quel niveau d'effort vous voulez fournir pour diminuer la probabilité de subir une perte. Les niveaux d'effort sont représentés par des nombres entiers entre 0 et 20, 0 représentant l'absence d'effort et 20 étant le niveau d'effort maximal que vous pouvez fournir. Attention, tout effort a un coût pour vous. En fonction du niveau d'effort fourni, le coût sera plus ou moins grand. Par contre, plus votre niveau d'effort est élevé, plus la probabilité que la perte se produise est faible. Pendant l'expérience vous pourrez choisir votre niveau d'effort à l'aide d'un curseur de défilement (un slider) comme celui présenté ci-dessous. Afin de vous aider à comprendre comment le niveau d'effort choisi impacte la probabilité de dommage, un graphique de type « camembert » sera présenté à l'écran et vous permettra de voir de manière interactive le lien entre le niveau d'effort choisi et la probabilité du dommage, ainsi que le coût associé à votre effort.

La prime d'assurance. La prime d'assurance que vous devez obligatoirement payer au début de chaque période pour vous assurer contre le risque de pertes va dépendre de la survenance du dommage. Autrement dit, la prime à payer à la période suivante dépendra de la survenance ou non du dommage pendant la période en cours. Sachez que la prime pour la première période est la même pour tout le monde, car aucun dommage n'a encore pu avoir lieu. Cette prime de départ est fixée à **12 ECU**. A partir de la période 2, chaque prime d'assurance va dépendre du dommage éventuel en période précédente. Plus précisément, si vous ne subissez pas de dommage pendant la période en cours, la prime de la période suivante sera de **0,40 ECU**. Néanmoins, si vous subissez un dommage, la prime de la période suivante sera de **40 ECU**.

En résumé, à chaque période vous devez décider quel niveau d'effort vous voulez fournir sachant que l'effort a un coût mais il diminue la probabilité que vous subissiez une perte. Ensuite, une fois que la prime d'assurance et le coût sont payés, le dommage peut se réaliser, ce qui entraînera une perte monétaire qui ne sera couverte que partiellement par votre assurance. Enfin, en fonction de votre expérience individuelle au cours de la période, la prime d'assurance à la période suivante sera calculée. La survenance d'un dommage entraînera une augmentation de la prime pour la période suivante. L'absence du dommage entraînera une baisse de la prime pour la période suivante. Le résumé de ces informations sera affiché à l'écran à la fin de chaque période.

Vos gains. A la fin de l'expérience, une des périodes sera tirée au hasard pour déterminer votre gain pour cette partie. Ce gain ne vous sera communiqué qu'à la toute fin de l'expérience. Ainsi, votre gain potentiel dépendra de la prime d'assurance que vous payez, du coût de l'effort et du dommage éventuel. Par exemple, supposons que votre prime d'assurance à payer pour la période est de 40 ECU et vous ne faites aucun effort pour réduire la probabilité du dommage. Si le dommage se produit, votre gain potentiel (si cette période est tirée au hasard pour la rémunération) sera de :

500 (dotation) - 40 (prime) - 300 (dommage) + 200 (indemnisation) = 360 ECU

Si au contraire, vous faites un effort de niveau 10 qui vous coûte 6,5 ECU pour réduire la probabilité que le dommage ait lieu et que le dommage ne se réalise pas, votre gain potentiel sera de:

500 (dotation) – 40 (prime) – 6,50 (coût de l'effort de 10) = 453,5 ECU

Et si vous faites un effort de niveau 10 mais le dommage se réalise tout de même, votre gain potentiel sera de :

500 (dotation) – 40 (prime) – 6,50 (coût de l'effort) – 300 (dommage) + 200 (indemnisation) = 353,50 ECU"

Part 2

"La tâche à réaliser dans cette partie est identique à la Partie 1 et le taux de conversion qui s'applique est toujours de **1€= 75 ECU**. Cependant, avant de commencer les 8 périodes de la Partie 2, vous aurez une possibilité de changer de type de contrat d'assurance, si vous le souhaitez. Dans la Partie 1, la prime d'assurance que vous deviez payer à chaque période dépendait uniquement de la survenance ou non d'un dommage au cours de la période précédente. Ainsi, il y avait deux niveaux de prime possibles, **0,40 et 40 ECU**, sans compter le niveau de départ commun à tout le monde. Vous pouvez garder ce type de contrat dans la Partie 2. Vous avez cependant la possibilité d'opter pour un nouveau type de contrat. Si vous optez pour ce nouveau type de contrat, la prime d'assurance que vous allez payer ne dépendra plus de la survenance ou non d'un dommage. La prime pour la période en cours sera déterminée entièrement par l'effort de prévention que vous avez fourni pendant la période précédente. En effet, dans ce nouveau type de contrat d'assurance, votre assureur aura l'information sur votre effort de prévention. Selon le niveau d'effort plus ou moins grand que vous fournirez, vous payerez une prime plus ou moins grande. Le tableau ci-dessous vous donne les informations sur les différents niveaux de prime en fonction de votre niveau d'effort.

les niveaux d'effort	0	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20
le coût de l'effort	0	0,07	0,26	0,59	1,04	1,63	2,34	3,19	4,16	5,27	6,50	7,87	9,36	10,99	12,74	14,63	16,64	18,79	21,06	23,47	26,00
la prime d'assurance	40,00	31,15	27,48	24,66	22,29	20,20	18,31	16,57	14,96	13,44	12,00	10,63	9,33	8,08	6,87	5,71	4,58	3,49	2,43	1,40	0,40

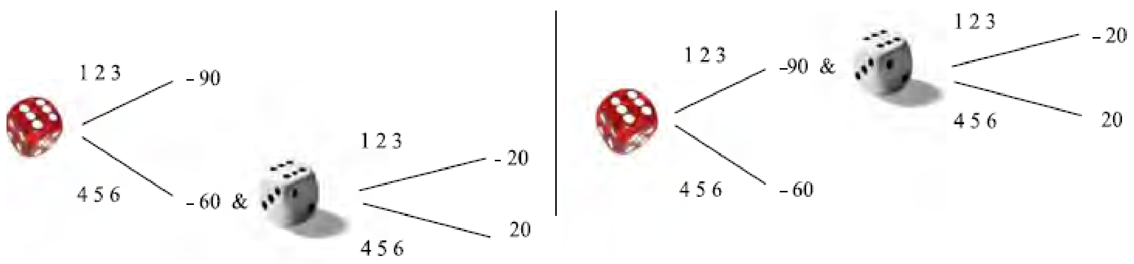
Vous pourrez de nouveau voir à l'écran à l'aide d'un slider comment la prime à payer, le coût de l'effort et la probabilité de dommage varient en fonction de votre niveau d'effort choisi.

Quel que soit le contrat que vous choisissez pour cette Partie 2, la prime pour la première période de cette nouvelle partie sera toujours la même pour tout le monde (**12 ECU**). En effet, si vous gardez le même type de contrat que pendant la Partie 1, aucun dommage n'a encore été enregistré pour cette nouvelle partie de l'expérience. Et si vous optez pour le nouveau type de contrat, l'assureur n'a pas encore pu observer l'effort que vous décidez de fournir. Dans ce deuxième cas, votre effort de prévention sera pris en compte dans le calcul de la prime à partir de la deuxième période. Quel que soit le contrat que vous choisissez, 100 ECU resteront à votre charge si un dommage survient. Une fois que vous avez fait votre choix de contrat d'assurance, vous participerez à 8 périodes de choix comme lors de la Partie 1. De la même manière, à la fin de cette partie, une des périodes sera tirée au hasard pour déterminer votre gain. Ce gain ne vous sera communiqué qu'à la toute fin de l'expérience."

Part 3

"Pour cette Partie 3, le taux de conversion qui s'applique est de **1€= 25 ECU**. Au début de la partie, vous recevrez une dotation de **165 ECU**. Ensuite, vous allez devoir prendre cinq décisions. Ces décisions concerneront des choix entre deux options, appelées «**option A**» et «**option B**».

Exemple : Supposons que vous avez le choix entre l'option A et l'option B ci-dessous:



Option A (à gauche). Vous avez trois issues possibles :

- vous avez une chance sur deux de perdre 90 ECU (si le dé rouge était lancé et que les chiffres 1, 2 ou 3 apparaissaient alors vous perdriez 90);

- vous avez une chance sur deux de perdre 60 ECU (si le dé rouge était lancé et que les chiffres 4, 5 ou 6 apparaissaient alors vous perdriez 60) et une chance sur deux de perdre 20 ECU de plus (si le dé blanc était lancé et que les chiffres 1, 2 ou 3 apparaissaient alors vous perdriez 20);

- vous avez une chance sur deux de perdre 60 ECU (si le dé rouge était lancé et que les chiffres 4, 5 ou 6 apparaissaient alors vous perdriez 60) et une chance sur deux de gagner 20 ECU (si le dé blanc était lancé et que les chiffres 4, 5 ou 6 apparaissaient alors vous gagneriez 20).

Option B (à droite). Vous avez trois issues possibles :

- vous avez une chance sur deux de perdre 60 ECU : si le dé rouge était lancé et que les chiffres 4, 5 ou 6 apparaissaient alors vous perdriez 60) ;

- vous avez une chance sur deux de perdre 90 ECU (si le dé rouge était lancé et que les chiffres 1, 2 ou 3 apparaissaient alors vous perdriez 90) et une chance sur deux de perdre 20 ECU de plus (si le dé blanc était lancé et que les chiffres 1, 2 ou 3 apparaissaient alors vous perdriez 20);

- vous avez une chance sur deux de perdre 90 ECU (si le dé rouge était lancé et que les chiffres 1, 2 ou 3 apparaissaient alors vous perdriez 90) et une chance sur deux de gagner 20 ECU (si le dé blanc était lancé et que les chiffres 4, 5 ou 6 apparaissaient alors vous gagneriez 20).

Pour chacune des cinq décisions, des instructions apparaîtront sur votre écran pour vous rappeler les choix. Une fois une décision validée, une nouvelle décision vous sera présentée.

A la fin de l'expérience, une décision parmi les cinq sera tirée au hasard afin de déterminer vos gains pour cette partie. Vous procéderez ensuite au lancer virtuel de dés pour déterminer votre gain étant donné la décision tirée au sort et le choix que vous avez fait pour cette décision."

Part 4

"Dans cette Partie 4, l'unité monétaire est l'euro.

Durant cette partie, vous aurez **au plus trois** séries de décisions à prendre. La dotation pour chaque série de décisions vous sera précisée à l'écran.

Chaque décision consistera à choisir entre deux options, appelées «**Loterie A**» et «**Loterie B**». Pour chaque ligne de décision, les deux options consistent en la possibilité de perdre (ou gagner) des montants différents, toujours avec une chance sur deux. Vous devez indiquer quelle option vous préférez.

Exemple d'une série de décisions à prendre avec une chance sur deux de **perdre** un montant X ou Y :

Remarque: Durant cette Partie 4, vous ne pouvez pas prendre de décisions incohérentes. Plus précisément, si vous préférez la *Loterie A* à la Loterie B pour une ligne donnée, alors la Loterie A sera automatiquement sélectionnée comme préférée pour toutes les lignes *précédentes*. De même, si vous préférez la *Loterie B* à la Loterie A pour une ligne donnée, alors la Loterie B sera sélectionnée comme préférée pour toutes les lignes *suivantes*. Il se peut donc que l'ordinateur modifie vos choix dans ce sens durant vos prises de décision. Vous pouvez également voir cette série de décisions à prendre comme une seule décision : indiquer la ligne, à laquelle vous préférez passer de la Loterie A à la Loterie B pour toutes les lignes suivantes.

Vous êtes dans la partie 4, série 1

Veuillez choisir entre la loterie A et la loterie B.

Vous recevez une dotation de 5€ pour cette série.

Loterie A	A	B	Loterie B
50% de chance de perdre -2,4€ et 50% de perdre -1,6€	○	○	50% de chance de perdre -4,9€ et 50% de perdre -0,75€
50% de chance de perdre -2,32€ et 50% de perdre -1,6€	○	○	50% de chance de perdre -4,5€ et 50% de perdre -0,75€
50% de chance de perdre -2,24€ et 50% de perdre -1,6€	○	○	50% de chance de perdre -3,54€ et 50% de perdre -0,75€
50% de chance de perdre -2,16€ et 50% de perdre -1,6€	○	○	50% de chance de perdre -3,14€ et 50% de perdre -0,75€
50% de chance de perdre -2,08€ et 50% de perdre -1,6€	○	○	50% de chance de perdre -2,86€ et 50% de perdre -0,75€
50% de chance de perdre -2€ et 50% de perdre -1,6€	○	○	50% de chance de perdre -2,65€ et 50% de perdre -0,75€
50% de chance de perdre -1,92€ et 50% de perdre -1,6€	○	○	50% de chance de perdre -2,48€ et 50% de perdre -0,75€
50% de chance de perdre -1,84€ et 50% de perdre -1,6€	○	○	50% de chance de perdre -2,32€ et 50% de perdre -0,75€
50% de chance de perdre -1,76€ et 50% de perdre -1,6€	○	○	50% de chance de perdre -2,17€ et 50% de perdre -0,75€
50% de chance de perdre -1,68€ et 50% de perdre -1,6€	○	○	50% de chance de perdre -2,01€ et 50% de perdre -0,75€

Valider

Toutes les séries de décisions consisteront à choisir entre une Loterie A et une Loterie B. Les séries ne dépendent pas l'une de l'autre.

A la fin de l'expérience, *une des séries sera tirée au hasard.* Ensuite, une des lignes de cette série sera choisie au hasard. Enfin, en fonction de l'option (Loterie A ou Loterie B) que vous avez choisi pour cette ligne, vous allez procéder au tirage dans l'urne virtuelle afin de déterminer votre gain final pour cette partie."

C.3 Non-parametric analysis: results of additional Mann-Whitney tests

Table C.1: Treatment differences in Part 1

	T1-T2	T1-T3	T1-T4	T2-T3	T2-T4	T3-T4
Z	-0.076	-1.383	1.469	-1.675	1.812	3.272
p-value	0.9396	0.1668	0.1419	0.0939	0.0700	**0.0011**

Table C.2: Treatment differences in Part 2 per contract type

	T1-T2	T1-T3	T1-T4	T2-T3	T2-T4	T3-T4
BM	**0.0451**	0.8836	0.2616	0.2202	0.3908	0.5246
BC	0.4628	0.8471	**0.00336**	0.4039	**0.00049**	**1.467e-0.5**

Table C.3: Contract differences per part and per treatment

	BM1-BM2	BC1-BC2	BM1-BC1	BM2-BC2
T1	0.9732	0.889	**0.01517**	**0.01909**
T2	0.6649	0.4277	**0.00103**	**0.00014**
T3	0.9015	0.178	0.1838	0.1003
T4	0.7732	0.2481	0.5282	0.5522

Table C.4: Treatment differences per chosen contract

	T1-T2	T1-T3	T1-T4	T2-T3	T2-T4	T3-T4
BM1 (P1)	**0.08195**	0.8692	0.5159	0.2537	0.3222	0.8071
BM2 (P2)	**0.0451**	0.8836	0.2616	0.2202	0.3908	0.5246
BC1 (P1)	0.1052	0.2059	**0.007586**	0.4582	**0.005567**	**0.000925**
BC2 (P2)	0.4628	0.8471	**0.00336**	0.4039	**0.00049**	**1.467e-0.5**

General conclusion

This thesis aims at improving the understanding of the impact that new data has on the insurance sector by examining the potential changes brought by the current development of digital technologies. It specifically focuses on the consequences that this transformation and the information availability might have on risk classification and risk prevention. The present conclusion provides an overview of the main results and contributions of this work and potential directions for further research on this issue.

Chapter 1 contributes to the analysis and better understanding of the global impact that new data has on the insurance sector. We provide a discussion on how new data can affect two important aspects of insurance functioning, namely risk classification and risk prevention.

The mere existence of debates around the question of risk classification and individualization attests to the complexity of the subject which extends to other domains outside of the insurance practice. For instance, the notion of fair premiums and fairness itself is an intricate notion, with significant divergence between the concepts of social fairness and individual fairness. While cross-subsidization is considered unfair for the low-risk agents, the classification based on any characteristic is inevitably unfair at least to some individuals involved.

This chapter contributes to the discussion on societal issues stemming from data availability. Nevertheless, our analysis could benefit greatly from an extended exploration of the societal perspective, which is an important area of further research and reflection. For instance, regardless of the arguments we make, risk-adequate premiums *can* make coverage inaccessible or unaffordable for some groups of the population, and specifically for the less wealthy high-risk individuals.

Considering risk prevention, from the societal perspective, the debate on the effectiveness and attractiveness of behavioral contracts compared to bonus-malus contracts can be linked to the discussion on the "objectivity" of risk classification factors. On the one hand, it can be perceived as unfair to penalize a policyholder based on the fact that the accident has occurred. On the other hand, the idea of sanctioning the absence of preventive effort as opposed to the accidents implies judging on something that did not occur (yet), which can also be perceived as unfair. Discussions in the public, the academic, and the policy regulation fields are needed to assess the benefits and address the concerns related to the possibility of using individual information on behavior to price insurance contracts.

Advanced analytical tools and more detailed data allow, in theory, to move towards more individualized insurance contracts, both in terms of coverage and premium. In particular, insurers might offer personalized services suited to the needs of each policyholder, but also set more risk-adequate premiums by creating more risk groups, and the possibility of increased price differentiation is viewed as a threat to the mutualization principle of risk pooling. Those issues are examined in Chapter 2 and Chapter 3.

After presenting the context and discussing two main issues of interest, we proceed by exploring the first, namely the risk classification, in Chapter 2. We contribute to the questions concerning personalization and risk classification, in particular regarding high-risk agents, by showing that the agents that are revealed to be high risks and the new low-risk policyholders are equally important for the insurer from the point of view of solvency constraints.

We introduce heterogeneous risks and two types of risk loading in the analysis, to take into account the size, the combination of risk types, and their contribution to the buffer fund through the loaded premiums. Loaded premiums enable the accumulation of a buffer fund used to manage the probability of insolvency, and we consider both the additive and the multiplicative risk loadings.

We show that it is not necessarily desirable for the insurer to form a homogeneous pool of low-risk policyholders, at least from the regulatory perspective. We consider independent high and low risks and we obtain our results first for binary distributed, and then for normally distributed risks, showing that in the binary case, high-risk agents contribute proportionally more to the control of the probability of insolvency, compared to the low-risk agents. Thus, it is not necessarily desirable for the insurer to form a homogeneous pool of low-risk policyholders, at least from the regulatory perspective. We conclude that the information on the individual risks can be used to lower the probability of insurer's insolvency by decreasing the high-risk agents' exposure to the individual risk.

The work presented in Chapter 2 can benefit from considering other possible discrete claims distributions. Indeed, binary distribution can be a baseline example, while a normal distribution can be a plausible approximation for sufficiently big portfolios, yet it can be insightful to build a similar analysis for other cases. Another interesting avenue of research is to consider both sides of insurance contracting at the same time because the insurance premium size and the probability of insolvency can both affect the policyholders' willingness to pay.

Further, from the policyholders' point of view, it is important to consider not only the probability but also the impact of insurers' insolvency. Indeed, if the insurer is insolvent, the resulting coverage will be only partial. We consider this dimension in Chapter 3, where we discuss the implications that partial coverage has on the optimal choice of the insurer's type for a heterogeneous population of agents seeking to insure their risk.

In Chapter 3, we continue to investigate the potential impact of risk classification and personalization enabled by data availability. In Chapter 2 we explored the potential impact on the high-risk agents, while in Chapter 3 we turn to the investigation regarding low-risk agents, challenging the idea that the individualization of insurance premiums is advantageous for private stock insurers and low-risk agents. As previously, we assume that information is symmetrical due to the new data on individual characteristics and actions, and, as a consequence, that it is possible to perfectly differentiate risk types.

We introduce a mutual insurer that differs from the stock insurer in two main points. We consider the stock insurer charging individualized insurance premiums, and the mutual insurer exerting less price differentiation. We also include in our analysis the second dimension of interest, which is the probability of insolvency. While mutual insurers can manage the possibility of insolvency ex-post by issuing a call for additional premiums, the stock insurers manage their probability of insolvency ex-ante by charging a risk loading on top of the pure premium. This allows the stock insurers to restrict the probability of insolvency to the desirable level, which can be suggested by the regulator (0.5% at the European level with Solvency II Directive).

We show that the low-risk agents are not necessarily better off with a stock insurance contract even if the stock insurer is informed about their low-risk type. For a given level of the probability of insolvency, the size of the stock insurance risk loading is determined by the number of policyholders. If the low-risk group is small, the associated size of the risk loading might provide low risks the incentive to join the mutual pool with the high-risk agents.

Our analysis provided in this chapter can be enriched in multiple ways. First, we assume that the capital is normalized to zero both for the stock and the mutual insurer. Including the capital in the analysis can provide more detailed results, even if changing this assumption would not necessarily reverse the results that we obtain.

If both insurers have the equivalent positive amount of capital at the beginning of the period, and the amount of capital is high enough so that the probability of insolvency is sufficiently low even without the risk loading, the mutual insurance will be always preferred by a homogeneous population. If we assume that only the stock insurer collects capital through the external stockholders before selling policies, it will decrease the stock insurer's probability of insolvency, and the condition for the mutual insurer to be preferred will be harder to be met.

Second, we assume that the mutual insurer exerts only negative premium adjustments. However, mutuals belong to their policyholders. Consequently, the latter can equally receive ex-post discounts in case of a financial surplus, if such a possibility is specified by the mutual policy. In this case, there is a possibility of both negative and positive ex-post premium adjustments. Our results can be extended to such contracts, which are in fact fully participating policies. The assumption of positive adjustment would relax the condition on the critical values by making the mutual insurer more attractive.

Finally, it can be interesting to model a continuum of risk types rather than only high-risk and low-risk agents. Additionally, while it substantially complicates the analysis, a possible avenue for further research would be to relax the assumption of simultaneity of choice made by an entire risk group. Making use of simulations to examine the parameters such that mutual insurance is preferred by the entire population can also be an interesting idea for further exploration.

Another possible avenue that we find interesting is to explore the potential of mutual insurance to provide incentives for prevention in the experimental setting. Indeed, the actual choice between mutual and stock insurance might also depend on social preferences. Hence, the decision to choose mutual insurance can be determined by the preferences for solidarity or by the sense of personal engagement, rather than by the risk level itself. The mutual insurers may therefore be more efficient in promoting preventive activities, which is an interesting question for further research.

We show in this chapter that the existence of the pooling equilibrium with both high-risk and low-risk agents choosing the mutual insurer depends on the relative size of each group in the population. Naturally, it also depends on the distance between the two risk levels. The closer the two groups are in terms of the individual probability of loss, the higher is the range of values allowing for the existence of the pooling equilibrium. As a result, current data availability could serve to promote self-protection and help policyholders to lower their risk exposure, as examined in Chapter 4.

In Chapter 4, we analyze how the contract type affects the policyholders' preventive actions, namely the effort provided to reduce the probability of an accident. We also examine the potential determinants of contract choice, when a bonus-malus and a behavioral contract are offered to the policyholders.

We provide a theoretical framework to compare both contract types. We derive a series of predictions concerning the optimal prevention effort and the comparison between two contracts, which serve to articulate the hypotheses that we further test in our experiment. In particular, we test whether the subjects provide more prevention effort with a behavioral contract, whether an accident has an impact on the prevention in the following period, and whether risk aversion and prudence affect the level of effort provided in the experiment.

We build our experimental procedure as an individual choice of prevention investment under different experimental treatments. Treatments differ by the initial loss probability and the cost. All the subjects start with a bonus-malus contract and have to choose their level of prevention effort in each period. The premium for each next period is based on the accident occurrence during the previous period. After eight periods, all the subjects have a choice to keep the bonus-malus contract or switch to the behavioral contract entirely based on their effort provision. We additionally elicit subjects' risk aversion in gains and losses, as well as their degree of absolute risk aversion and prudence.

We find that the subjects choosing the behavioral contract provide higher levels of prevention effort than the subjects choosing a bonus-malus contract. We also observe self-selection in terms of contract choice according to the individual preferences for prevention. The subjects who provide a higher level of effort in the first part of the experiment, choose to continue with a behavioral contract, while those who provide low effort prefer to keep a bonus-malus contract. Nevertheless, we find that the choice of contract type is a significant determinant of the provision of prevention effort, even if we control for the average level of effort provided during the first part of the experiment.

Considering the impact of an accident on the prevention effort in the following period, our findings are not clear. The loss occurrence is a significant determinant of the effort in the first part of the game, but less so in the second part. Besides, our results also confirm the theoretical findings that the prevention effort depends on risk aversion and prudence. In particular, we find that risk-seeking individuals provide less effort to decrease their loss probability, and the same holds for more prudent subjects.

Our research on the prevention and behavioral contracts could benefit from adding additional experimental sessions for the following reason. In our experimental setting, all the subjects have started with a bonus-malus contract. To make a definite conclusion on the prevention incentives provided by a behavioral contract, it would be useful to add one or two additional sessions with all the subjects starting with a behavioral contract. This would enable us to confirm or reject the observation we currently have: the prevention effort seems to be mostly determined by the initial individual preferences, while the contract type has less impact.

There is still a lot to explore to provide a better understanding of the impact that new data has or might have on the insurance sector and society as a whole. Further research is needed on the issues presented in this thesis and on other questions stemming from the current development of digital technologies. Nevertheless, this work provided insights on the potential impact on high and low risks' coverage and on the possible consequences for the co-existence and the comparative benefits of mutual and stock insurance in the light of an enhanced risk segmentation, which becomes technically possible today. Finally, our work provided an examination of the insurance contracts entirely based on the individual behavior and the impact of their potential introduction on the choice of contract type and the risk prevention.

Conclusion générale

Cette thèse vise à améliorer la compréhension de l'impact des nouvelles données sur le secteur de l'assurance en examinant les changements potentiels apportés par le développement actuel des technologies numériques. Elle se concentre spécifiquement sur les conséquences que cette transformation et la disponibilité de l'information pourraient avoir sur la segmentation et la prévention des risques. La présente conclusion donne une vue d'ensemble des principaux résultats et contributions de ce travail et des directions potentielles pour des recherches ultérieures sur cette question.

Le Chapitre 1 contribue à l'analyse et à une meilleure compréhension de l'impact global des nouvelles données sur le secteur de l'assurance. Nous présentons une discussion sur la manière dont les nouvelles données peuvent affecter deux aspects importants du fonctionnement de l'assurance, à savoir la segmentation des risques et la prévention des risques.

La simple existence de débats autour de la question de la segmentation et de l'individualisation des risques témoigne de la complexité du sujet qui s'étend à d'autres domaines en dehors de la pratique de l'assurance. Par exemple, les notions de prime juste et équitable et d'équité elle-même sont des concepts complexes, avec une divergence importante entre les concepts d'équité sociale et d'équité individuelle. Si la subvention croisée est considérée comme injuste pour les agents à bas risque, la segmentation basée sur toute caractéristique est inévitablement injuste, au moins pour certains individus concernés.

Ce chapitre contribue à la discussion sur les questions sociétales provenant de la disponibilité des données. Néanmoins, notre analyse pourrait grandement bénéficier d'une exploration approfondie de la perspective sociétale, qui est un domaine important de recherche et de réflexion. Par exemple, quels que soient les arguments que nous avançons, des primes adaptées au risque peuvent rendre la couverture inaccessible ou inabordable pour certains groupes de la population, et plus particulièrement pour les individus à haut risque moins fortunés.

En ce qui concerne la prévention des risques, du point de vue de la société, le débat sur l'efficacité et l'attrait des contrats comportementaux par rapport aux contrats bonus-malus peut être lié à la discussion sur l'objectivité des facteurs de segmentation des risques. D'une part, il peut être perçu comme injuste de pénaliser un assuré sur la base du fait que l'accident s'est produit. D'autre part, l'idée de sanctionner l'absence d'effort de prévention par rapport aux accidents implique de juger de quelque chose qui ne s'est pas (encore) produit, ce qui peut également être perçu comme injuste. Des discussions dans les domaines public, universitaire et celui de la réglementation politique sont nécessaires pour évaluer les avantages potentiels et répondre aux préoccupations liées à la possibilité d'utiliser des informations individuelles sur le comportement pour fixer le prix des contrats d'assurance.

Des outils analytiques avancés et des données plus détaillées permettent, en théorie, de faire évoluer l'offre vers des contrats d'assurance plus individualisés, tant en termes de couverture que de prime. En particulier, les assureurs pourraient offrir des services personnalisés adaptés aux besoins de chaque assuré, mais aussi fixer des primes plus individualisées, en créant davantage de groupes de risques. Une telle possibilité de différenciation augmentée des prix est considérée comme une menace pour le principe de mutualisation des risques. Ces questions sont examinées dans les Chapitres 2 et 3.

Après avoir présenté le contexte et discuté des deux principales questions d'intérêt, nous procédons à l'exploration de la première, à savoir la segmentation des risques, dans le Chapitre 2. Nous contribuons aux questions relatives à la personnalisation et à la segmentation des risques, en particulier en ce qui concerne les agents à haut risque, en montrant que les agents qui se révèlent être à haut risque et les nouveaux assurés à bas risque sont tout aussi importants pour l'assureur du point de vue des contraintes de solvabilité.

Nous introduisons dans notre analyse des risques hétérogènes et deux types de chargement de prime, afin de prendre en compte la taille, la combinaison des types de risque et leur contribution au fond de sécurité à travers les primes chargées. Les primes chargées permettent la création d'un fonds de sécurité et l'accumulation des réserves utilisés pour gérer la probabilité d'insolvabilité, et nous considérons à la fois les chargement additif et multiplicatif.

Nous montrons qu'il n'est pas nécessairement souhaitable pour l'assureur de former un pool homogène d'assurés à bas risque, du moins du point de vue réglementaire. Nous considérons des hauts et des bas risques indépendants et nous obtenons nos résultats d'abord pour une distribution binaire des risques, puis pour des risques normalement distribués, montrant que dans le cas binaire, les agents à haut risque contribuent proportionnellement plus au contrôle de la probabilité d'insolvabilité, par rapport aux agents à bas risque. Ainsi, il n'est pas nécessairement souhaitable pour l'assureur de former un pool homogène d'assurés à bas risque, du moins du point de vue réglementaire. Nous concluons que l'information sur les risques individuels peut être utilisée pour réduire la probabilité d'insolvabilité de l'assureur en diminuant l'exposition des agents à haut risque.

Le travail présenté dans le Chapitre 2 peut bénéficier de la prise en compte d'autres distributions discrètes de sinistres. En effet, la distribution binaire sert d'un exemple de base, tandis que la distribution normale est une approximation plausible pour des portefeuilles suffisamment grands. Néanmoins, il peut être intéressant de construire une analyse similaire pour d'autres cas de figure. Une autre piste de recherche consiste à considérer les deux parties d'un contrat d'assurance en même temps, car le montant de la prime d'assurance et la probabilité d'insolvabilité peuvent tous deux affecter la propension à payer des assurés.

De plus, du point de vue des assurés, il est important de considérer non seulement la probabilité, mais aussi l'impact de l'insolvabilité des assureurs. En effet, si l'assureur est insolvable, la couverture reçue par les assurés sera partielle. Nous considérons cette dimension dans le Chapitre 3, où nous discutons les implications qu'une couverture partielle a sur le choix optimal du type d'assureur pour une population hétérogène d'agents cherchant à assurer leur risque.

Dans le Chapitre 3, nous continuons à étudier l'impact potentiel de la segmentation des risques et de la personnalisation rendue possible par la disponibilité des données. Dans le Chapitre 2, nous avons exploré l'impact potentiel sur les agents à haut risque, tandis que dans le Chapitre 3, nous nous tournons vers l'étude des agents à bas risque, en remettant en question l'idée que l'individualisation des primes d'assurance est avantageuse pour les assureurs privés et les agents à bas risque. Comme précédemment, nous supposons que l'information est symétrique, en raison de la disponibilité des données sur les caractéristiques et les actions individuelles, et, par conséquent, qu'il est possible de différencier parfaitement les types de risque.

Nous introduisons un assureur mutualiste qui diffère de l'assureur privé par actions sur deux points principaux. Nous considérons que l'assureur privé demande des primes d'assurance individualisées, tandis que l'assureur mutualiste pratique une moindre différenciation des prix. Nous incluons également dans notre analyse la deuxième dimension d'intérêt, à savoir la probabilité d'insolvabilité. Alors que les mutuelles peuvent gérer leur probabilité d'insolvabilité *ex post* en faisant un recours à un rappel de cotisations, les assureurs privés gèrent leur probabilité d'insolvabilité *ex ante* en rajoutant un chargement de prime à la prime pure. Cela permet aux assureurs privés de limiter la probabilité d'insolvabilité au niveau souhaitable, qui peut être exigé par le régulateur (0,5% au niveau européen avec la directive Solvabilité II).

Nous montrons que les agents à bas risque ne sont pas nécessairement mieux lotis avec un contrat d'assurance classique même si l'assureur privé est informé de leur type de risque. Pour un niveau donné de probabilité d'insolvabilité, la taille du chargement de la prime pratiqué par l'assureur privé est déterminée par le nombre d'assurés dans son portefeuille. Si le groupe d'assurés à bas risque est petit, le montant du chargement associée pourrait inciter les bas risques à rejoindre la mutuelle avec les agents à haut risque.

Notre analyse, présentée dans ce chapitre, peut être enrichie de plusieurs façons. Premièrement, nous supposons que le capital est normalisé à zéro à la fois pour l'assureur par actions et pour l'assureur mutualiste. L'introduction du capital dans l'analyse peut fournir des résultats plus détaillés, même si cela n'impacterait pas fondamentalement les résultats que nous obtenons. Si les deux assureurs détiennent le même niveau de capital au début de l'exercice, et le montant du capital est suffisamment élevé pour que la probabilité d'insolvabilité soit suffisamment faible même sans l'application du chargement, alors la mutuelle sera toujours préférée par une population homogène. Si nous supposons que seul l'assureur privé collecte du capital par le biais d'actionnaires externes avant de vendre des contrats, la condition pour que la mutuelle soit préférée sera plus difficile à remplir.

Deuxièmement, nous supposons que l'assureur mutualiste n'exerce que des rappels de cotisations qui sont des ajustements de primes négatifs. Cependant, les mutuelles appartiennent à leurs assurés. Par conséquent, ces derniers peuvent également recevoir des dividendes en cas d'excédent financier, si cette possibilité est prévue par la politique de la mutuelle. Dans ce cas, il existe une possibilité d'ajustement de primes *ex post* négatif et positif. Nos résultats peuvent être étendus à de tels contrats, qui sont en fait des contrats participatifs. L'hypothèse d'un ajustement positif assouplirait la condition concernant les seuils critiques et rendrait l'assureur mutualiste plus attractif.

Enfin, il peut être intéressant de modéliser un continuum de types de risque. En outre, bien que cela complique considérablement l'analyse, une voie possible pour des recherches plus approfondies serait de relâcher l'hypothèse de simultanéité des choix effectués par un groupe de risque entier. L'utilisation de simulations afin d'examiner les paramètres tels que l'assurance mutuelle soit préférée par l'ensemble de la population peut également être une idée intéressante pour une exploration plus approfondie.

Une autre piste que nous trouvons intéressante est d'explorer dans le cadre expérimental le potentiel de l'assurance mutuelle à fournir des incitations à la prévention. En effet, le choix réel entre l'assurance mutuelle et celle par actions pourrait dépendre des préférences sociales. Ainsi, la décision de choisir l'assurance mutuelle peut être déterminée par les préférences pour la solidarité ou par le sentiment d'engagement personnel, plutôt que par le niveau de risque. Les assureurs mutualistes peuvent donc être plus efficaces dans la promotion des activités préventives.

Nous montrons dans ce chapitre que l'existence d'une situation telle que des agents à haut et bas risque choisissent de manière optimale la mutuelle dépend de la taille relative de chaque groupe dans la population. Naturellement, elle dépend aussi de la différence entre les deux niveaux de risque. Plus les deux groupes sont proches en termes de probabilité individuelle de perte, plus la fourchette de valeurs permettant l'existence d'un tel équilibre mélangé est large. Par conséquent, la disponibilité actuelle des données pourrait servir à promouvoir l'auto-protection et à aider les assurés à réduire leur exposition au risque, ce qui est examiné dans le Chapitre 4.

Dans le Chapitre 4, nous analysons la façon dont le type de contrat affecte le niveau de prévention des assurés, à savoir l'investissement dans l'effort pour réduire la probabilité d'un accident. Nous examinons également les déterminants potentiels du choix du contrat, lorsqu'un bonus-malus et un contrat comportemental sont proposés aux assurés.

Nous fournissons un cadre théorique pour comparer les deux types de contrats. Nous dérivons une série de prédictions concernant l'effort de prévention optimal et la comparaison entre deux contrats, qui servent à articuler les hypothèses que nous testons ensuite dans notre expérience. En particulier, nous examinons si les sujets fournissent plus d'effort de prévention avec un contrat comportemental, si un accident a un impact sur la prévention dans la période suivante, et si l'aversion au risque et la prudence affectent le niveau d'effort fourni dans l'expérience.

Nous développons notre procédure expérimentale basée sur un jeu de choix individuel d'investissement de prévention avec des différents groupes de traitements expérimentaux. Les traitements diffèrent par la probabilité de perte initiale et par le coût de l'effort. Tous les sujets commencent avec un contrat bonus-malus et doivent choisir leur niveau d'effort de prévention à chaque période. La prime pour chaque période suivante est basée sur le nombre d'accidents survenus au cours de la période précédente. Après huit périodes, tous les sujets ont le choix de conserver le contrat bonus-malus ou de choisir le contrat comportemental basé sur le niveau d'effort. Nous élicitons en outre l'aversion au risque des sujets et leur prudence.

Nous constatons que les sujets qui choisissent le contrat comportemental fournissent des niveaux d'effort de prévention plus élevés que les sujets qui choisissent le contrat bonus-malus. Nous observons également une auto-sélection en termes de choix de contrat en fonction des préférences individuelles pour la prévention. Les sujets qui fournissent un niveau d'effort plus élevé dans la première partie de l'expérience, choisissent de poursuivre avec un contrat comportemental, tandis que ceux qui fournissent un niveau d'effort plus faible préfèrent conserver un contrat bonus-malus. Néanmoins, nous constatons que le choix du type de contrat impacte l'effort de prévention fourni, même quand on contrôle pour le niveau moyen d'effort fourni pendant la première partie de l'expérience.

En ce qui concerne l'impact d'un accident sur l'effort de prévention au cours de la période suivante, nos conclusions ne sont pas claires. L'occurrence de la perte est un déterminant significatif de l'effort dans la première partie du jeu, mais moins dans la deuxième partie. Par ailleurs, nos résultats confirment également les conclusions théoriques selon lesquelles l'effort de prévention dépend de l'aversion au risque et de la prudence. En particulier, nous constatons que les individus averses au risque fournissent moins d'effort pour diminuer leur probabilité de perte, et il en va de même pour les sujets plus prudents.

Notre recherche sur la prévention et les contrats comportementaux pourrait certainement bénéficier de l'ajout de sessions expérimentales supplémentaires. Dans notre cadre expérimental, tous les sujets ont commencé avec un contrat bonus-malus. Afin de fournir une conclusion définitive sur les incitations à la prévention fournies par un contrat comportemental, il serait utile d'ajouter une session supplémentaire avec tous les sujets commençant par un contrat comportemental. Cela nous permettrait de confirmer ou d'infirmer l'observation que nous avons actuellement : l'effort de prévention semble être principalement déterminé par les préférences individuelles initiales, tandis que le type de contrat a un impact moindre.

Il reste encore plein de pistes à explorer pour s'approcher de la meilleure compréhension de l'impact que les nouvelles données ont ou pourraient avoir sur le secteur de l'assurance et sur la société dans son ensemble. Des recherches supplémentaires sont nécessaires, que ce soit sur les questions présentées dans cette thèse ou sur d'autres questions découlant du développement actuel des technologies numériques. Néanmoins, ce travail a fourni un nombre de résultats quant à l'impact potentiel de la disponibilité des données sur la couverture des hauts et des bas risques et sur les conséquences possibles concernant la coexistence et les avantages comparatifs de l'assurance mutuelle et de l'assurance par actions, à la lumière d'une segmentation des risques plus fine qui devient techniquement possible aujourd'hui. Enfin, notre travail a permis d'examiner les contrats entièrement basés sur le comportement individuel et l'impact de leur introduction potentielle sur le choix de contrat d'assurance et sur la prévention des risques.

Bibliography

Abbring, J. H., Chiappori, P.-A., and Pinquet, J., “Moral hazard and dynamic insurance data”, *Journal of the European Economic Association*, vol. 1.4, pp. 767–820, 2003 (cit. on pp. 21, 32, 122, 127).

Abbring, J. H., Chiappori, P.-A., and Zavadil, T., “Better safe than sorry? Ex ante and ex post moral hazard in dynamic insurance data”, 2008 (cit. on pp. 21, 32, 122, 127).

Acemoglu, D., Makhdoumi, A., Malekian, A., and Ozdaglar, A., *Too much data: Prices and inefficiencies in data markets*, tech. rep., National Bureau of Economic Research, 2019 (cit. on p. 56).

Agarwal, V. and Ligon, J. A., “Insurer contract nonperformance in a market with adverse selection”, *Journal of Risk and Insurance*, pp. 135–150, 1998 (cit. on p. 94).

Akerlof, G. A., “The Market for "Lemons": Quality uncertainty and the Market Mechanism”, *The Quarterly Journal of Economics*, vol. 84.3, pp. 488–500, 1970 (cit. on pp. 15, 25, 38, 63).

Alary, D., Gollier, C., and Treich, N., “The effect of ambiguity aversion on insurance and self-protection”, *The Economic Journal*, vol. 123.573, pp. 1188–1202, 2013 (cit. on p. 126).

Albrecht, P. and Huggenberger, M., “The fundamental theorem of mutual insurance”, *Insurance: Mathematics and Economics*, vol. 75, pp. 180–188, 2017 (cit. on pp. 18, 29, 66, 67).

Barry, L. and Charpentier, A., “Personalization as a promise: Can Big Data change the practice of insurance?”, *Big Data & Society*, vol. 7.1, 2020 (cit. on p. 54).

Bergemann, D., Bonatti, A., and Gan, T., “The economics of social data”, 2020 (cit. on p. 56).

Berger, L., “The impact of ambiguity and prudence on prevention decisions”, *Theory and Decision*, vol. 80.3, pp. 389–409, 2016 (cit. on p. 57).

Borch, K., *Economics of Insurance, Vol. 29 of Advanced Textbooks in Economics*, 1990 (cit. on p. 66).

Borch, K., “Equilibrium in a Reinsurance Market”, *Econometrica*, vol. 30.3, pp. 424–444, 1962 (cit. on pp. 65, 90).

Bourlès, R., "On the emergence of private insurance in presence of mutual agreements", 2009 (cit. on pp. 20, 30, 97).

Bourlès, R. and Henriet, D., "Risk-sharing Contracts with Asymmetric Information", *The Geneva Risk and Insurance Review*, vol. 37.1, pp. 27–56, 2012 (cit. on p. 90).

Boyer, M. and Dionne, G., "An empirical analysis of moral hazard and experience rating", *The Review of Economics and Statistics*, pp. 128–134, 1989 (cit. on p. 127).

Braun, A., Schmeiser, H., and Rymaszewski, P., "Stock vs. mutual insurers: Who should and who does charge more?", *European Journal of Operational Research*, vol. 242.3, pp. 875–889, 2015 (cit. on pp. 20, 30, 97).

Briys, E. and Schlesinger, H., "Risk aversion and the propensities for self-insurance and self-protection", *Southern Economic Journal*, pp. 458–467, 1990 (cit. on pp. 58, 94, 125, 135).

Brockett, P. L., "On the misuse of the central limit theorem in some risk calculations", *The Journal of Risk and Insurance*, vol. 50.4, pp. 727–731, 1983 (cit. on pp. 68, 81).

Brunette, M. and Jacob, J., "Risk aversion, prudence and temperance: An experiment in gain and loss", *Research in Economics*, vol. 73.2, pp. 174–189, 2019 (cit. on pp. 22, 33, 123, 141).

Cevolini, A. and Esposito, E., "From pool to profile: Social consequences of algorithmic prediction in insurance", *Big Data & Society*, vol. 7.2, 2020 (cit. on p. 54).

Charpentier, A., "Le bonus-malus français a-t-il encore un avenir?", 2010 (cit. on pp. 127, 128).

Charpentier, A., David, A., and Elie, R., "Optimal claiming strategies in Bonus Malus systems and implied Markov chains", *Risks*, vol. 5.4, p. 58, 2017 (cit. on p. 128).

Charpentier, A. and Denuit, M., "Mathématiques de l'assurance non-vie", *Economica, Paris*, 2005 (cit. on p. 37).

Charpentier, A., Denuit, M., and Elie, R., "Segmentation et Mutualisation, les deux faces d'une même pièce?", *Risques*, vol. 103, pp. 19–23, 2015 (cit. on p. 54).

Charpentier, A. and Le Maux, B., "Natural catastrophe insurance: How should the government intervene?", *Journal of Public Economics*, vol. 115.C, pp. 1–17, 2014 (cit. on pp. 20, 30, 98, 106, 115).

Chiappori, P.-A., Macho, I., Rey, P., and Salanié, B., "Repeated moral hazard: The role of memory, commitment, and the access to credit markets", *European Economic Review*, vol. 38.8, pp. 1527–1553, 1994 (cit. on p. 127).

Corcos, A., Pannequin, F., and Montmarquette, C., "Leaving the market or reducing the coverage? A model-based experimental analysis of the demand for insurance", *Experimental Economics*, vol. 20.4, pp. 836–859, 2017 (cit. on p. 124).

Courbage, C., Loubergé, H., and Peter, R., "Optimal prevention for multiple risks", *Journal of risk and insurance*, vol. 84.3, pp. 899–922, 2017 (cit. on p. 126).

Courbage, C. and Rey, B., "On the willingness to pay to reduce risks of small losses", *Journal of Economics*, vol. 95.1, pp. 75–82, 2008 (cit. on p. 126).

Courbage, C. and Rey, B., "Optimal prevention and other risks in a two-period model", *Mathematical Social Sciences*, vol. 63.3, pp. 213–217, 2012 (cit. on p. 126).

Courbage, C., Rey, B., and Treich, N., "Prevention and precaution", in: *Handbook of insurance*, Springer, 2013, pp. 185–204 (cit. on pp. 57, 124, 131).

Crainich, D., Eeckhoudt, L., and Hammitt, J., "The value of risk reduction: new tools for an old problem", *Theory and Decision*, vol. 79.3, pp. 403–413, 2015 (cit. on p. 126).

Crainich, D., Eeckhoudt, L., and Trannoy, A., "Even (mixed) risk lovers are prudent", *American Economic Review*, vol. 103.4, pp. 1529–35, 2013 (cit. on p. 136).

Csermely, T. and Rabas, A., "How to reveal people's preferences: Comparing time consistency and predictive power of multiple price list risk elicitation methods", *Journal of Risk and Uncertainty*, vol. 53.2-3, pp. 107–136, 2016 (cit. on p. 142).

Cummins, J. D., "Insurer's Risk: A Restatement", *The Journal of Risk and Insurance*, vol. 41.1, pp. 147–157, 1974 (cit. on pp. 18, 29, 67, 68).

Cummins, J. D., "Statistical and financial models of insurance pricing and the insurance firm", *The Journal of Risk and Insurance*, vol. 58.2, pp. 261–302, 1991 (cit. on pp. 18, 28, 29, 67).

Cummins, J. D. and Mahul, O., "Optimal insurance with divergent beliefs about insurer total default risk", *Journal of Risk and Uncertainty*, vol. 27.2, pp. 121–138, 2003 (cit. on p. 93).

Dachraoui, K., Dionne, G., Eeckhoudt, L., and Godfroid, P., "Comparative mixed risk aversion: definition and application to self-protection and willingness to pay", *Journal of Risk and Uncertainty*, vol. 29.3, pp. 261–276, 2004 (cit. on pp. 125, 126).

Denuit, M., Eeckhoudt, L., Liu, L., and Meyer, J., "Tradeoffs for downside risk-averse decision-makers and the self-protection decision", *The Geneva Risk and Insurance Review*, vol. 41.1, pp. 19–47, 2016 (cit. on pp. 58, 126).

Denuit, M., Eeckhoudt, L., and Menegatti, M., "A Note on Subadditivity of Zero-Utility Premiums", *ASTIN Bulletin: The Journal of the IAA*, vol. 41.1, pp. 239–250, 2011 (cit. on pp. 68, 81).

Denuit, M., Guillen, M., and Trufin, J., "Multivariate credibility modeling for usage-based motor insurance pricing with behavioural data", *Annals of Actuarial Science, 2019, vol. 13, num. 2, p. 378-399*, 2019 (cit. on pp. 58, 122).

Diamond, D. W., "Financial intermediation and delegated monitoring", *The review of economic studies*, vol. 51.3, pp. 393–414, 1984 (cit. on p. 68).

Dionne, G. and Eeckhoudt, L., "Self-insurance, self-protection and increased risk aversion", *Economics Letters*, vol. 17.1-2, pp. 39–42, 1985 (cit. on pp. 58, 124).

Dionne, G. and Lasserre, P., "Adverse selection, repeated insurance contracts and announcement strategy", *The Review of Economic Studies*, vol. 52.4, pp. 719–723, 1985 (cit. on p. 127).

Dionne, G. and Li, J., "The impact of prudence on optimal prevention revisited", *Economics Letters*, vol. 113.2, pp. 147–149, 2011 (cit. on p. 125).

Dionne, G., Michaud, P.-C., and Dahchour, M., "Separating moral hazard from adverse selection and learning in automobile insurance: longitudinal evidence from France", *Journal of the European Economic Association*, vol. 11.4, pp. 897–917, 2013 (cit. on pp. 21, 32, 122, 127).

Dionne, G., Pinquet, J., Maurice, M., and Vanasse, C., "Incentive mechanisms for safe driving: a comparative analysis with dynamic data", *The review of Economics and Statistics*, vol. 93.1, pp. 218–227, 2011 (cit. on p. 127).

Dionne, G. and Vanasse, C., "Automobile insurance ratemaking in the presence of asymmetrical information", *Journal of Applied Econometrics*, vol. 7.2, pp. 149–165, 1992 (cit. on p. 127).

Doherty, N. A. and Dionne, G., "Insurance with Undiversifiable Risk: Contract Structure and Organizational Form of Insurance Firms", *Journal of Risk and Uncertainty*, vol. 6.2, pp. 187–203, 1993 (cit. on pp. 98, 109).

Doherty, N. A. and Schlesinger, H., "Rational Insurance Purchasing: Consideration of Contract Nonperformance", *The Quarterly Journal of Economics*, vol. 105.1, pp. 243–253, 1990 (cit. on pp. 89, 94).

Drichoutis, A. C. and Lusk, J. L., "What can multiple price lists really tell us about risk preferences?", *Journal of Risk and Uncertainty*, vol. 53.2-3, pp. 89–106, 2016 (cit. on pp. 22, 33, 123, 142, 143).

Eckert, J. and Gatzert, N., "Risk-and value-based management for non-life insurers under solvency constraints", *European Journal of Operational Research*, vol. 266.2, pp. 761–774, 2018 (cit. on p. 70).

Eeckhoudt, L., Godfroid, P., and Gollier, C., "Willingness to pay, the risk premium and risk aversion", *Economics Letters*, vol. 55.3, pp. 355–360, 1997 (cit. on p. 125).

Eeckhoudt, L. and Gollier, C., "The impact of prudence on optimal prevention", *Economic Theory*, vol. 26.4, pp. 989–994, 2005 (cit. on pp. 125, 126).

Eeckhoudt, L., Gollier, C., and Schlesinger, H., *Economic and financial decisions under risk*, Princeton University Press, 2011 (cit. on pp. 58, 125, 135).

Eeckhoudt, L., Huang, R. J., and Tzeng, L. Y., "Precautionary effort: a new look", *Journal of Risk and Insurance*, vol. 79.2, pp. 585–590, 2012 (cit. on p. 126).

Eeckhoudt, L. and Schlesinger, H., "Putting risk in its proper place", *American Economic Review*, vol. 96.1, pp. 280–289, 2006 (cit. on p. 141).

Eeckhoudt, L. and Spaeter, S., "La dictature des 3 P: Prévention, Prudence, Précaution", 2013 (cit. on p. 126).

Ehrlich, I. and Becker, G. S., "Market insurance, self-insurance, and self-protection", *Journal of political Economy*, vol. 80.4, pp. 623–648, 1972 (cit. on pp. 57, 124).

EIOPA, *Big Data Analytics in motor and health insurance: a thematic review*, tech. rep., European Insurance and Occupational Pensions Authority, 2019, URL: https://www.eiopa.europa.eu/sites/default/files/publications/eiopa_bigdataanalytics_thematicreview_april2019.pdf (cit. on pp. 14, 24, 40).

EIOPA, *Failures and near misses in insurance: overview of the causes and early identification*, Report, Luxembourg: Publications Office of the European Union, 2018 (cit. on p. 109).

European Commission, *A Europe fit for the digital age*, tech. rep., European Commission, 2019, URL: https://ec.europa.eu/info/strategy/priorities-2019-2024/europe-fit-digital-age_en (cit. on pp. 13, 23).

European Commission, *A European strategy for data*, tech. rep., European Commission, Directorate-General for Communications Networks, Content and Technology, 2020, URL: https://eur-lex.europa.eu/legal-content/EN/ALL/?uri=CELEX:52020DC0066 (cit. on pp. 14, 24).

European Commission, *Digital economy and society statistics: households and individuals*, tech. rep., European Commission, 2020, URL: https://ec.europa.eu/eurostat/statistics-explained/index.php/Digital_economy_and_society_statistics_-_households_and_individuals (cit. on pp. 13, 23).

Fagart, M.-C., Fombaron, N., and Jeleva, M., "Risk mutualization and competition in insurance markets", *The Geneva Papers on Risk and Insurance Theory*, vol. 27.2, pp. 115–141, 2002 (cit. on pp. 20, 30, 90, 98, 110).

FCA, *Call for Inputs on Big Data in retail general insurance*, tech. rep., Financial Conduct Authority, 2016, URL: https://www.fca.org.uk/publication/feedback/fs16-05.pdf (cit. on pp. 41, 42).

Feller, W., *An Introduction to Probability Theory and Its Applications*, John Wiley & Sons, 1968 (cit. on p. 68).

Friesen, G., "On the Lack of Participating Policy Usage by Stock Insurance Companies", *Journal of Risk and Insurance*, vol. 74.1, pp. 185–206, 2007 (cit. on p. 96).

Gajdos, T., Huber, H., Massoni, S., and Vergnaud, J.-C., "Health insurance: an experimental approach", 2014 (cit. on p. 124).

Gatzert, N. and Schmeiser, H., "The merits of pooling claims revisited", *The Journal of Risk Finance*, vol. 13.3, pp. 184–198, 2012 (cit. on pp. 18, 29, 66, 67).

Gollier, C., "Insurance and precautionary capital accumulation in a continuous-time model", *Journal of Risk and Insurance*, pp. 78–95, 1994 (cit. on p. 137).

granularity, n. In: *Cambridge Advanced Learner's Dictionary & Thesaurus*, Cambridge University Press, 2013, URL: `https://dictionary.cambridge.org/dictionary/english/granularity` (visited on 10/22/2020) (cit. on p. 40).

Guillen, M., Nielsen, J. P., Pérez-Marín, A. M., and Elpidorou, V., "Can automobile insurance telematics predict the risk of near-miss events?", *North American Actuarial Journal*, vol. 24.1, pp. 141–152, 2020 (cit. on p. 59).

Hamwi, I. S., Hudson, T., and Chen, Y., "Solvency regulation in the property-liability insurance industry", *International Advances in Economic Research*, vol. 10.4, pp. 313–327, 2004 (cit. on p. 95).

Harrington, J. L., *Relational database design and implementation*, Morgan Kaufmann, 2016 (cit. on p. 40).

Henriet, D. and Rochet, J.-C., "La logique des systèmes bonus-malus en assurance automobile: une approche théorique", *Annales d'Économie et de Statistique*, pp. 133–152, 1986 (cit. on p. 128).

Hofmann, A. and Peter, R., "Self-Insurance, Self-Protection, and Saving: On Consumption Smoothing and Risk Management", *Journal of Risk and Insurance*, vol. 83.3, pp. 719–734, 2016 (cit. on p. 126).

Hölmstrom, B., "Moral hazard and observability", *The Bell journal of economics*, pp. 74–91, 1979 (cit. on pp. 15, 25).

Holt, C. A. and Laury, S. K., "Risk aversion and incentive effects", *American economic review*, vol. 92.5, pp. 1644–1655, 2002 (cit. on p. 142).

Houston, D. B., "Risk, insurance, and sampling", *The Journal of Risk and Insurance*, vol. 31.4, pp. 511–538, 1964 (cit. on pp. 67, 68).

IAIS, *Issues Paper on the Use of Big Data Analytics in Insurance*, tech. rep., International Association of Insurance Supervisors, 2020, URL: `https://www.iaisweb.org/page/supervisory-material/issues-papers/file/89244/issues-paper-on-use-of-big-data-analytics-in-insurance` (cit. on pp. 40, 43, 60).

Jindapon, P., "Do risk lovers invest in self-protection?", *Economics Letters*, vol. 121.2, pp. 290–293, 2013 (cit. on p. 136).

Jullien, B., Salanie, B., and Salanie, F., "Should more risk-averse agents exert more effort?", *The Geneva Papers on Risk and Insurance Theory*, vol. 24.1, pp. 19–28, 1999 (cit. on pp. 125, 131).

Kahneman, D. and Tversky, A., "Prospect theory: an analysis of decision under risk", *Econometrica*, vol. 47.2, pp. 263–291, 1979 (cit. on p. 70).

Keller, B., Eling, M., Schmeiser, H., et al., "Big data and insurance: implications for innovation, competition and privacy", *The Geneva Association*, vol. 33, 2018 (cit. on pp. 42, 44, 51).

Klein, F. and Schmeiser, H., "Optimal Risk Pools under Changing Volatility and Heterogeneous Risk Classes", Working Paper on Risk Management and Insurance, 2018 (cit. on p. 70).

Klein, R., "Insurance Regulation and the Challenge of Solvency II: Modernizing the System of US Solvency Regulation", *Public policy papers of the National Association of Mutual Insurance Companies*, 2012 (cit. on p. 80).

Krieger, M. and Mayrhofer, T., "Prudence and prevention: An economic laboratory experiment", *Applied Economics Letters*, vol. 24.1, pp. 19–24, 2017 (cit. on p. 124).

Laux, C. and Muermann, A., "Financing risk transfer under governance problems: Mutual versus stock insurers", *Journal of Financial Intermediation*, vol. 19.3, pp. 333–354, 2010 (cit. on pp. 89, 97).

Lee, K., "Background risk and self-protection", *Economics Letters*, vol. 114.3, pp. 262–264, 2012 (cit. on p. 126).

Lee, K., "Uncertain indemnity and the demand for insurance", *Theory and decision*, vol. 73.2, pp. 249–265, 2012 (cit. on pp. 89, 93).

Lee, K., "Wealth effects on self-insurance and self-protection against monetary and nonmonetary losses", *The Geneva Risk and Insurance Review*, vol. 30.2, pp. 147–159, 2005 (cit. on p. 134).

Lemaire, J., *Bonus-malus systems in automobile insurance*, tech. rep., 1995 (cit. on pp. 127, 128).

Ligon, J. A. and Thistle, P. D., "Moral hazard and background risk in competitive insurance markets", *Economica*, vol. 75.300, pp. 700–709, 2008 (cit. on pp. 20, 30, 96).

Ligon, J. A. and Thistle, P. D., "The Formation of Mutual Insurers in Markets with Adverse Selection", *The Journal of Business*, vol. 78.2, pp. 529–556, 2005 (cit. on pp. 19, 30, 90, 96).

Lorson, J., Schmeiser, H., and Wagner, J., "Evaluation of benefits and costs of insurance regulation–a conceptual model for Solvency II", *Journal of Insurance Regulation*, vol. 31.1, pp. 125–156, 2012 (cit. on p. 70).

Masuda, T. and Lee, E., "Higher order risk attitudes and prevention under different timings of loss", *Experimental Economics*, vol. 22.1, pp. 197–215, 2019 (cit. on p. 124).

Mayers, D. and Smith, C., "Ownership structure across lines of property-casualty insurance", *The Journal of Law and Economics*, vol. 31.2, pp. 351–378, 1988 (cit. on pp. 20, 30, 95).

Menegatti, M., "Optimal prevention and prudence in a two-period model", *Mathematical Social Sciences*, vol. 58.3, pp. 393–397, 2009 (cit. on p. 126).

Menegatti, M. and Rebessi, F., "On the substitution between saving and prevention", *Mathematical Social Sciences*, vol. 62.3, pp. 176–182, 2011 (cit. on p. 126).

Meyer, D. J. and Meyer, J., "A Diamond-Stiglitz approach to the demand for self-protection", *Journal of Risk and Uncertainty*, vol. 42.1, pp. 45–60, 2011 (cit. on p. 126).

Meyers, G. and Van Hoyweghen, I., "'Happy failures': Experimentation with behaviour-based personalisation in car insurance", *Big Data & Society*, vol. 7.1, 2020 (cit. on pp. 55, 58).

Milgrom, P. R., "Good news and bad news: Representation theorems and applications", *The Bell Journal of Economics*, pp. 380–391, 1981 (cit. on p. 59).

Mimra, W., Nemitz, J., and Waibel, C., "Voluntary pooling of genetic risk: A health insurance experiment", *Journal of Economic Behavior & Organization*, 2019 (cit. on p. 124).

Mimra, W. and Wambach, A., "Endogenous Insolvency in the Rothschild–Stiglitz Model", *Journal of Risk and Insurance*, 2017 (cit. on pp. 15, 25, 59, 94, 96).

Mol, J. M., Botzen, W. W., and Blasch, J. E., "Risk reduction in compulsory disaster insurance: Experimental evidence on moral hazard and financial incentives", *Journal of Behavioral and Experimental Economics*, vol. 84, p. 101500, 2020 (cit. on p. 124).

Mullainathan, S. and Obermeyer, Z., "Does machine learning automate moral hazard and error?", *American Economic Review*, vol. 107.5, pp. 476–80, 2017 (cit. on p. 43).

Noussair, C. N., Trautmann, S. T., and Van de Kuilen, G., "Higher order risk attitudes, demographics, and financial decisions", *Review of Economic Studies*, vol. 81.1, pp. 325–355, 2014 (cit. on pp. 22, 33, 123, 141).

OECD, *Technology and innovation in the insurance sector*, tech. rep., Organisation for Economic Co-operation and Development, 2017, URL: https://www.oecd.org/pensions/Technology-and-innovation-in-the-insurance-sector.pdf (cit. on pp. 49, 121).

OECD, *The Impact of Big Data and Artificial Intelligence in the Insurance Sector*, tech. rep., Organisation for Economic Co-operation and Development, 2020, URL: https://www.oecd.org/finance/The-Impact-Big-Data-AI-Insurance-Sector.pdf (cit. on p. 43).

Pannequin, F., Corcos, A., and Montmarquette, C., “Are insurance and self-insurance substitutes? An experimental approach”, *Journal of Economic Behavior & Organization*, 2019 (cit. on p. 124).

Patil, S. V., Vieider, F., and Tetlock, P. E., “Process versus outcome accountability”, *The Oxford handbook of public accountability*, pp. 69–89, 2014 (cit. on p. 59).

Peter, R., “Optimal self-protection in two periods: On the role of endogenous saving”, *Journal of Economic Behavior & Organization*, vol. 137, pp. 19–36, 2017 (cit. on p. 126).

Picard, P., “Equilibrium in insurance markets with adverse selection when insurers pay policy dividends”, *Journal of Risk and Insurance*, vol. 86.4, pp. 887–914, 2019 (cit. on pp. 15, 25).

Picard, P., “Participating Insurance Contracts and the Rothschild-Stiglitz Equilibrium Puzzle”, *The Geneva Risk and Insurance Review*, vol. 39.2, pp. 153–175, 2014 (cit. on pp. 15, 20, 25, 30, 96).

Porat, M. M. and Powers, M. R., “What Is “Insurance”? Lessons From The Captive Insurance Tax Controversy”, *Risk Management and Insurance Review*, vol. 2.2, pp. 72–80, 1999 (cit. on p. 68).

Powers, M. R., “An insurance paradox”, *The Journal of Risk Finance*, vol. 7.2, pp. 113–116, 2006 (cit. on p. 69).

Powers, M. R., Venezian, E. C., and Jucá, I. B., “Of happy and hapless regulators: the asymptotics of ruin”, *Insurance: Mathematics and Economics*, vol. 32.2, pp. 317–330, 2003 (cit. on p. 67).

Rees, R., Gravelle, H., and Wambach, A., “Regulation of insurance markets”, *The Geneva Papers on Risk and Insurance Theory*, vol. 24.1, pp. 55–68, 1999 (cit. on pp. 89, 95).

Robinson, P. J. and Botzen, W. J. W., “Economic experiments, hypothetical surveys and market data studies of insurance demand against low-probability/high-impact risks: A systematic review of designs, theoretical insights and determinants of demand”, *Journal of Economic Surveys*, vol. 33.5, pp. 1493–1530, 2019 (cit. on p. 124).

Rothschild, M. and Stiglitz, J., “Equilibrium in competitive insurance markets: An essay on the economics of imperfect information”, in: *Uncertainty in economics*, Elsevier, 1978, pp. 257–280 (cit. on pp. 15, 25, 38, 89, 94).

Rothschild, M. and Stiglitz, J., “Increasing risk: I. A definition”, *Journal of Economic theory*, vol. 2.3, pp. 225–243, 1970 (cit. on p. 125).

Rubinstein, A. and Yaari, M. E., “Repeated insurance contracts and moral hazard”, *Journal of Economic theory*, vol. 30.1, pp. 74–97, 1983 (cit. on p. 128).

Samuelson, P., “Risk and uncertainty: A fallacy of large numbers”, 1963 (cit. on p. 68).

Schlesinger, H. and Schulenburg, J. G. v. d., "Risk aversion and the purchase of risky insurance", *Journal of Economics*, vol. 47.3, pp. 309–314, 1987 (cit. on pp. 93, 94).

Seog, S. H., "Insurance markets with differential information", *Journal of Risk and Insurance*, vol. 76.2, pp. 279–294, 2009 (cit. on p. 90).

Siegelman, P., "Information & equilibrium in insurance markets with big data", *Conn. Ins. LJ*, vol. 21, p. 317, 2014 (cit. on p. 57).

Smith, B. and Stutzer, M., "A theory of mutual formation and moral hazard with evidence from the history of the insurance industry", *The Review of Financial Studies*, vol. 8.2, pp. 545–577, 1995 (cit. on pp. 19, 30, 96).

Smith, B. and Stutzer, M., "Adverse selection, aggregate uncertainty, and the role for mutual insurance contracts", *Journal of Business*, pp. 493–510, 1990 (cit. on pp. 19, 30, 90, 96).

Smith, M. and Kane, S., "The law of large numbers and the strength of insurance", in: *Insurance, risk management, and public policy*, Springer, 1994, pp. 1–27 (cit. on pp. 18, 29, 68, 76).

Snow, A., "Ambiguity aversion and the propensities for self-insurance and self-protection", *Journal of risk and uncertainty*, vol. 42.1, pp. 27–43, 2011 (cit. on p. 126).

Sweeney, G. H. and Beard, T. R., "The comparative statics of self-protection", *Journal of Risk and Insurance*, pp. 301–309, 1992 (cit. on p. 134).

Tapiero, C. S., Kahane, Y., and Jacque, L., "Insurance premiums and default risk in mutual insurance", *Scandinavian Actuarial Journal*, vol. 1986.2, pp. 82–97, 1986 (cit. on p. 93).

telematics, n. In: *Cambridge Advanced Learner's Dictionary & Thesaurus*, Cambridge University Press, 2013, URL: `https://dictionary.cambridge.org/dictionary/english/telematics` (visited on 10/22/2020) (cit. on p. 42).

Venezian, E. C., "Efficiency and equity in insurance", *The Journal of Risk and Insurance*, vol. 51.2, pp. 190–204, 1984 (cit. on p. 69).

Venezian, E. C., "Insurer capital needs under parameter uncertainty", *The Journal of Risk and Insurance*, pp. 19–32, 1983 (cit. on p. 68).

Villeneuve, B., "The consequences for a monopolistic insurance firm of evaluating risk better than customers: the adverse selection hypothesis reversed", *The Geneva Papers on Risk and Insurance Theory*, vol. 25.1, pp. 65–79, 2000 (cit. on pp. 52, 90).

Wakker, P., Thaler, R., and Tversky, A., "Probabilistic insurance", *Journal of Risk and Uncertainty*, vol. 15.1, pp. 7–28, 1997 (cit. on p. 70).

Wilson, C., "A model of insurance markets with incomplete information", *Journal of Economic theory*, vol. 16.2, pp. 167–207, 1977 (cit. on p. 94).

Zimmer, A., Gründl, H., Schade, C. D., and Glenzer, F., "An incentive-compatible experiment on probabilistic insurance and implications for an insurer's solvency level", *Journal of Risk and Insurance*, vol. 85.1, pp. 245–273, 2018 (cit. on p. 70).

Zimmer, A., Schade, C., and Gründl, H., "Is default risk acceptable when purchasing insurance? Experimental evidence for different probability representations, reasons for default, and framings", *Journal of Economic Psychology*, vol. 30.1, pp. 11–23, 2009 (cit. on p. 70).

Acronyms

AI *Artificial Intelligence.* 43–45

EIOPA *European Insurance and Occupational Pensions Authority.* 108

FCA *Financial Conduct Authority.* 41, 42

GPS *Global Positioning System.* 40, 45, 48

IAIS International Association of Insurance Supervisors. 40

ICT *Information and communications technology.* 13, 14

IoT *Internet of Things.* 42, 45

PAYD *Pay-As-You-Drive.* 48, 121

PHYD *Pay-How-You-Drive.* 48, 58, 121

SCR *Solvency Capital Requirement.* 108

TIC *Technologies de l'information et de la communication.* 23, 24

UBI *Usage-Based Insurance.* 48–50, 56, 58, 121

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Résumé

Cette thèse vise à améliorer la compréhension des conséquences que la disponibilité de l'information pourrait avoir sur la segmentation et la prévention des risques. Le premier chapitre propose une discussion globale sur l'impact des nouvelles données sur le secteur de l'assurance. Le deuxième chapitre analyse la segmentation des risques et la conséquence pour les agents à haut risque dans un cadre théorique. Dans le troisième chapitre, nous nous tournons vers l'étude des agents à bas risque, toujours dans le cadre théorique, en remettant en question l'idée que l'individualisation des primes d'assurance est avantageuse pour les assureurs privés et les agents à bas risque. Dans le quatrième chapitre, nous analysons de manière théorique et expérimentale la façon dont le type de contrat affecte le niveau de prévention des assurés et les déterminants du choix du contrat. Ce travail offre un nombre de résultats concernant l'effet de la disponibilité des données sur la couverture des hauts et des bas risques, les conséquences possibles pour la coexistence de l'assurance mutuelle et de l'assurance classique, ainsi que les contrats basés sur le comportement individuel.

Mots-clés: assurance, information, segmentation, personnalisation, prévention

Information and insurance: risk classification and risk prevention in the context of data availability

Abstract

This thesis aims at improving the understanding of the consequences that the information availability might have on risk classification and risk prevention. The first chapter offers a global discussion on the impact that new data has on the insurance sector. The second chapter analyzes the risk classification regarding high-risk agents in particular, from the theoretical point of view. In the third chapter, we turn to the theoretical investigation regarding low-risk agents and challenge the idea that the individualization of insurance premiums is advantageous for private stock insurers and low-risk agents. In the fourth chapter, we analyze theoretically and experimentally how the contract type affects the policyholders' preventive actions, as well as the potential determinants of contract choice. This work provides a series of results regarding the potential impact of data availability on high and low risks' coverage, on the possible consequences for the co-existence and the comparative benefits of mutual and stock insurance in the light of enhanced risk segmentation, as well as the insurance contracts entirely based on the individual behavior.

Keywords: classification, information, insurance, personalization, prevention