Norwegian School of Economics
Bergen, December 2017

Asymmetric Information in Insurance

The Impact of Big Data on Low-SES Individuals

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Master's thesis in Economic Analysis

Norwegian School of Economics

Preface

This thesis has been an exciting project, as it covers a critical assessment of technological developments from a social point of view; a subject we find to be relevant for both businesses and private individuals. Moreover, we have enjoyed studying insurance literature and theory in depth, as we find it to be both highly interesting and challenging.

We would like to thank our supervisor, Ingvild Almås, for contributing with valuable insight and encouraging feedback in a process where the road was not always clear.

Abstract

In this thesis, we analyze the effect of big data in insurance markets with heterogeneous insurance takers. Through a theoretical approach, we consider the effects of increased information flows on insurance contracts offered to different types of individuals along dimensions of socioeconomic status and risk. We find that, on a general level, the development of big data, which is likely to alleviate problems of asymmetric information, will have unfavourable effects on individuals of low socioeconomic status. These effects arise due to a social gradient in risk or differences in abilities, or both.

Less asymmetric information leads to more actuarially fair pricing of individuals, holding each individual responsible for their own risk to a larger extent than before. We assess this from a normative perspective, and consider redistributory concerns.

Contents

1 Introduction

Economic progress rarely follows a predictable pattern. Trends are disrupted by revolutionary developments; both ideological and industrial which interplay with each other. Ideological developments open for new ways to technologically disrupt, while innovations bring up new questions of fairness and ethics.

Angus Deaton refers to these progressions as “great escapes”; developments that allow for increased well-being. In essence, these are what the collective society, as well as the individual, strives for. But as Deaton says, the nature of most escapes is that not everyone makes it. Some are left behind, and as such, inequality arises (Deaton, 2013). From the first agricultural revolution, where societies went from egalitarian hunter-gatherers to hierarchies with ownership and property, to the industrial revolutions, where capital exceeded labor in returns, winners and losers have come about. For each of these revolutions, we look back and consider whether it was worth it. Is the price of progress fair, and if not, what should be done?

We claim that we are standing on the brink of a new disruption, fueled by digitalization and connectivity. Klaus Schwab refers to this as the Fourth Industrial Revolution, characterized by a fusion of technologies that is blurring the lines between the physical, digital, and biological spheres. He claims it will be greater in scale, scope, and complexity than any transformations humankind has experienced before. Like with previous revolutions, societal concerns arise, and the greatest one associated with the current changes is inequality (Schwab, 2015).

1.1 Research Question

With this thesis, we aim to take a critical view on the developing technologies, and how they are used. Specifically, we consider the effects of higher degrees of information flow between firms and customers. We refer to this increased scope of information as big data, and assess how this phenomenon will affect individuals of different types. Further, we consider the fairness of wealth distributions that may arise as a consequence of big data usage.

The medium we limit our analysis to is the market for insurance. We do this because the insurance sector is one in which high levels of disruption is expected. Furthermore, insurance takers are priced differently, contingent on various characteristics observable for the insurance companies. Big data and increased access to personal information related to an individual's risk is argued to incentivize insurance companies to price insurance takers on a more individual level than before. We believe that this development may have different implications for different types of people along a socioeconomic dimension. For now we denote these types as having different socioeconomic status (SES), but we explain this in detail later.

The aim of this thesis is to answer the following question:

Will increased use of big data in insurance have unfavorable effects on insurance takers with low socioeconomic status?

1.2 Methodology

Empirical research on the effects of big data is limited, both because big data is difficult to define in various business contexts and that it is a relatively new concept, not yet implemented to a full extent in many industries. Due to the scope of this thesis, we will focus on the analysis using a theoretical approach. However, we do acknowledge that the effects of big data should, in addition, be assessed through a more empirical approach.

In our thesis we model an insurance market with heterogeneous insurance takers and a competitive insurance market. Specifically, we simulate how market outcomes change after an increased utilization of big data. We note that there are many uncertainties regarding the future and the effects of big data in the insurance market. We therefore construct a flexible framework that covers a wide array of plausible outcomes.

In parts of our model we include Rothschild and Stiglitz (1976) and Wilson (1977) and their notions of equilibrium in competitive insurance markets with asymmetric information. One notable difference from their approach is that we consider that insurance takers can differ in other ways than only their risk type by including a social dimension in which insurance takers also can differ in their socioeconomic status. First, we can use this dimension to include that individuals with a low socioeconomic status may more likely be of higher risk than their counterparts. Second, we can use these groupings to incorporate that the high-SES individuals may be privileged in the sense that they have opportunities, regarding the flow of information, that are exclusive to them.

In an insurance setting, it is reasonable to assume that the development of big data will reduce information asymmetry, making insurance companies better at predicting individual risk. This typically results in more personalized insurance contracts offered to certain individuals. We model this by introducing various concepts of signalling, allowing insurance takers to signal their risk type to the insurance companies in order to receive a new insurance contract. By comparing new contracts offered to various groups of insurance takers to initial contracts offered, we are able to asses who benefits and who does not benefit from this development. Finally, we consider the fairness of an outcome from a societal point of view.

We provide a general model for the insurance market as a whole, but we emphasize the impact big data may have on the market for health- and life-insurance. We aim at being as general as possible, but for specific examples and applications of our model we limit our discussion to the Norwegian insurance market.

1.3 Outline

This introductory chapter will be followed by a description of the insurance market, where we take a closer look at the consumers of insurance. In chapter 3 we assess how big data may influence the traditional insurance model and discuss various concerns of its use. In chapters 4 and 5 we present relevant literature and theory, before we in chapter 6 derive our theoretical model. Chapter 7 includes a discussion, where we consider implications of big data, as well as methodological concerns. Finally, in chapter 8, we conclude.

2 Insurance Markets

In defining the insurance market, we can look to the *Encyclopedia Britannica* as described by Boatright (2010) for a thorough definition of insurance:

A contract that, by redistributing risk among a large number of people, reduces losses from accidents incurred by an individual in return for a specified payment (premium). The insurer undertakes to pay the insured or his beneficiary a specified amount of money in the event that the insured suffers loss through the occurrence of an event covered by the insurance contract (policy). By pooling both the financial contributions and the risks of a large number of policyholders, the insurer is able to absorb losses much more easily than is the uninsured individual.

The pooling of risk works through a theoretical reliance on the law of large numbers. The law states that, given independent and identically distributed units, the actual loss will approach the expected loss as the number of units increases. An assumption made is then that insurance takers in a product segment are homogeneous in terms of their riskiness. As insurance companies have uncovered observable factors that correlate with risk, these factors have been used to segment insurance takers into more specific pools, so as to more closely satisfy the homogeneity assumption.

These are the basic mechanisms on which the insurance industry finds its basis. We will in the following describe in further detail the supply- and demand-side of the insurance market, so we have a clearer picture of the environment in which we want to model our phenomenon of big data.

2.1 Providers of Insurance

As we can understand, insurance and pooling of resources demand organization. Before the development of insurance companies, insurance in practice was enabled through dependence on communities and families. If a member of a community was struck by misfortune, the community could come together to help him. Trust and codependence were thus critical factors in insurance. Structures were later on formalized through collection of resources to participate in insurance schemes. Actuarial science (the application of mathematics and statistical methods to assess risk) became formalized in the seventeenth century, with advances such as John Graunt's "Bills of Mortality"; the first study of mortality rates of an entire community of people (Graunt, 1662). These scientific methods were then taken into use in calculating both how much an individual needed to be compensated in the face of an accident, as well as the premia required to cover this compensation. As insurance developed to become an industry, administrative costs and margins were covered by an additional cost to insurance takers. As time has passed, insurance suppliers have competed in refining and sophisticating their supply of insurance.

Some distinctions can be of use when we consider the supply of insurance. We can on a general level distinguish three major types of insurance: property and casualty insurance, health insurance and life insurance. The first refers to protection of one's property against serious loss, and can cover whatever there is a supply and demand of. Homeowner policies, personal auto policies and commercial liability insurance are a few typical varieties. Health insurance is designed to protect individuals from large economic losses brought about by medical care by covering the whole or a part of a person's incurred medical expenses. The third category, life insurance is closely related, but is designed to protect not the insurance taker herself, but others that are economically hurt by her death (Boatright, 2010).

We note that insurance may be offered to either individuals or to groups, where the latter typically occurs through employee groups or labor associations. We limit our analysis of insurance to that of individuals. This is due especially to the socioeconomic factor that we are interested in assessing, which is at its clearest when we assess individuals.

Another useful distinction is the nature of the supplier in the spectrum of private-public. Due to certain market inefficiencies, some argue that insurance is a good that must be provided publicly. Also, given a public supply of insurance, a question of financing arises. This debate is especially prominent in matters of health insurance. In Norway, health care is provided for everyone and is financed heavily through taxation, making it mandatory in nature. This has not come without problems, as there are a number of inefficiencies connected to full provision of health care, such as queues and slow treatment processes (Hoel & Sæther, 2003). Due to this, private health care has arisen to supplement the demand for quick and efficient treatment, and has in many cases been combined with private health insurance. Questions arise as to how insurance can most efficiently be provided, and the development of insurance technology is likely to impact the discussion.

2.2 Consumers of Insurance

We have discussed various types of insurance that may be supplied in a market, as well as various distinctions we find useful. We now turn to briefly discuss the demand for insurance, as well as characteristics of insurance takers relevant to this thesis.

2.2.1 Demand for Insurance

The desire to insure oneself from unfortunate outcomes has traditionally been explained by a diminishing marginal utility to goods. This is typically illustrated by a concave utility function, which shows that an individual will place higher value on a certain amount of a good than a lottery with the same expected value. We illustrate this in Figure 1. For a lottery $(x_1, x_2; p, 1-p), p \in (0,1)$, a consumer with diminishing marginal utility will prefer the expected value $E(x)$ of the lottery to the lottery itself. This implies what economists refer to as risk aversion; given the choice of an uncertain lottery and a certain reward with the same expected values, a risk-averse individual will prefer the certain choice. It can also be shown that a fixed amount, known as the certainty equivalent (CE), below the expected value of the lottery will yield the same utility for a consumer as the lottery. This forms the basis for the demand-side of the insurance market; individuals are willing to reduce their wealth in order to fix their economic outcomes across different states.

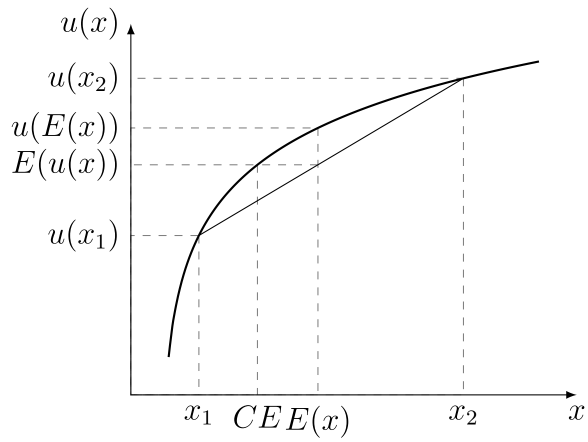


Figure 1: A concave utility function

With this, we have provided a theoretical basis for why we consider insurance a good. When we later model our insurance takers, we will include two sources of heterogeneity in insurance takers; risk profile and socioeconomic status. The former refers to how some individuals may be more likely to suffer losses than others, as well as higher levels contingent on a loss occurring. As we will discuss later, one's risk profile can, and often is argued, should be the basis in which an individual is priced in the insurance market. The latter refers a position on a socioeconomic stratum that in itself need not be relevant to the price an individual should face in the insurance market. Risk has a clear implication in insurance markets, while we claim SES may have a more complicated connection to insurance.

2.2.2 Socioeconomic Status (SES)

As our research question revolves around the effects big data can have on low-SES individuals, clarification on socioeconomic status is necessary, both to motivate our interest in the socioeconomic scale and to clarify a measure that does not necessarily have a clear definition.

As a point of departure, we may look to the Wiley Blackwell Encyclopedia of Health, Illness, Behavior (Baker, 2014). SES is generally defined as a measure of one's combined economic and social status (Galobardes, Shaw, Lawlor, Lynch, & Smith, 2006). It has thus usually been measured as a composite measure of income, education and occupation; all factors that we to some degree use to rank an individual's standing in society. A complication that arises in studying SES as a phenomenon, is the exact measure used: definitions of SES vary and depend on the research questions, the populations examined, and the measures available (Baker, 2014). Further, in order to make comparisons across groups, one needs to use measures that have the same implications across cultures and nations. Thus, we are left to use fairly rough proxies of SES that do not necessarily capture all that makes up for a socioeconomic rank. However, as a concept, most of us have an intuitive sense of what makes up a socioeconomic standing, as well as what may come with it. We find it meaningful in our discussion to view SES as a black-box type variable that enables certain individuals to achieve what others may not, be it through economic means, an advantage in relevant knowledge, or through advantageous socialization. This implies that there may be cases in which individuals are of different SES despite similar levels of income, education and profession.

In addition to our intuitive, and hopefully common, understanding of what SES may entail, we can use earlier studies of SES to our advantage as we attempt to answer our research question. In the following, we introduce social gradients; the idea that a variable may be related to inequalities in socioeconomic status.

2.2.3 The Social Gradient in Risk

We investigate the relationship between the risk of an insurance taker and her SES. We define this as the social gradient in risk, referring to the fact that inequalities in risk may be related to inequalities in social status.

In order to consider a social gradient in risk, we must first clarify what we mean by risk. In an insurance setting it will be natural to interpret an individual's risk as the expected loss[1] she faces. It is also convenient to translate this loss into monetary terms. This currency change is necessary in most settings, as it is usually the main means an insurance company uses to indemnify a claimant for her losses. Further, insurance is, as we have discussed, divided into categories, in which a loss along one dimension does not warrant an indemnity from another insurance type (one cannot make a claim for a broken leg on one's car insurance). Thus, it will be necessary to consider the social gradient in risk along different risk and insurance categories.

In a health- and life-insurance setting, the social gradient in risk will be closely related to the social gradient in health. The social gradient in health refers to the fact that people who are less well off have substantially shorter life expediencies and more illnesses than the rich (World Health Organization, 2003). Health indicators, such as life expectancy, number of deaths and number of different illnesses are often used in research of social inequalities in health. In addition, more indirect health indicators are used - such as welfare benefits and life-style related risk factors. Referring back to the Wiley Blackwell Encyclopedia of Health, Illness, Behavior, Baker (2014) states that the positive relationship between health and SES is viewed as a real phenomenon by many researchers and confirmed by numerous studies.

It follows that low-SES citizens will likely be offered a higher risk premium in these insurance settings. We check whether this is the case by listing different values for years

[1]The expected value of a random variable is given as the summation of each possible value the variable may take, weighted by the probability of the value occurring. It then follows that riskiness of an individual is a function of the probability of a loss, and the size of the loss contingent on it occurring.

of education and profession for different Norwegian insurance companies. Indeed, we find that there is a negative relationship between insurance premium and socioeconomic status for health- and life-insurance[2]. We implicitly make the assumption that this social gradient may hold even for unobservable SES-factors. This is equivalent to extrapolating the social gradient in risk for observables (such as education, income and occupation) to unobservable social factors (such as for example parents' education or other forms of social capital).

In the case of property- and casualty-insurance, the social gradient is less clear, mostly due to the many forms the insurance may come in. In cases in which the quality of the object insured reduces risk, such as cars with new technology, we can imagine that high-SES individuals will be less risky. When only the behaviour of the insurance taker affects the riskiness of the insured object, we cannot follow the same line of thinking. We thus do not make assumptions regarding social gradients in property- and casualty-insurance.

3 Big Data and the Insurance Market

We live in a world where data is generated at all times, and at an increasing rate due to technological development. Each decision made by a consumer on the Web generates a data point along different dimensions, and a growing number of commercial enterprises and authorities are discovering potential for strategic exploitation of these enormous data streams (Data Protection Authority, 2013). This data, and the opportunities that come with it, is now commonly referred to as "big data". There are several definitions available, and some are more technical than others. In this paper we will refer to big data in a more loosely defined term, and we find the following definition from Hurwitz, Nugent, Halper,

[2] Example from Gjensidige Forsikring: If you have primary school education and work with agriculture or forestry, you have to pay almost twice as much for disability income insurance as an individual with a masters degree who works in an office (Gjensidige Forsikring, 2017)
1: Age 24, primary school, agriculture and forestry, yearly income of 501-550 thousands, smoker, single, kids: NOK 507 per month.
2: Age 24, masters, office work, yearly income of 501-550 thousands, smoker, single, kids: NOK 254 per month.

and Kaufman suitable:

Big data is a combination of data-management technologies that have evolved over time. Big data enables organizations to store, manage, and manipulate vast amounts of data at the right speed and at the right time to gain the right insights (Hurwitz et al., 2013).

The phenomenon of big data and the opportunities to create business value from it, has led to a field of technical expertise in gathering, structuring and analyzing the increasingly available data. For society as a whole, both in the private and public sector, the value-creating potential of doing big data is expected to be large. Nevertheless, some sectors are said to be positioned for greater gains than others. Our motivation for writing about big data in the insurance industry is because this is a sector where big data is predicted to have a large impact. The McKinsey Global Institute (MGI) has defined a value potential index[3], where they find that the finance and insurance sector are positioned to benefit strongly from big data. Furthermore, MGI has identified some broadly applicable ways to leverage big data that offer transformational potential in creating value. This will have implications for how organizations will have to be designed, organized and managed. The ones we believe are most relevant for the insurance market are described in the following. First, insurance companies can map out highly specific segments and tailor products and services precisely designed to meet those needs. Second, insurance companies can substantially improve decision making by replacing or supplementing human decision-making with automated algorithms. Finally, big data can enable insurance companies to create new products and services, enhance existing ones, and even invent entirely new business models (McKinsey Global Institute, 2011).

Empirical research on the value-creating potential of doing big data is limited, due to the fact that it is difficult to define in various business contexts, and that it is a relatively new concept. Wamba, Akter, Edwards, Chopin, and Gnanzou (2015) perform a systematic review of research conducted on big data's potential impact. The findings

[3]The index consists of five metrics; 1) the amount of data available for use and analysis, 2) variability in performance, 3) number of stakeholders with which an organization deals on average, 4) transaction intensity, and 5) turbulence inherent in a sector.

show among other things that there are many avenues for exploring and conceptualizing the multifaceted nature of big data.

Further, Brynjolfsson, Hitt and Kim (2011) provide an overview of case-based evidence on how data-driven decision-making (DDD) affects firm performance. They go on to assess detailed survey data on the business practices and information technology investments of 179 large publicly traded firms in the US. Controlling for the endogeneity of DDD, they find that firms that adopt data-driven decision-making have output and productivity that is 5-6% higher than what would be expected given other investments and IT-usage (Brynjolfsson et al., 2011). This evidence points towards a desirability for implementing data-based analytics in decision making.

We will throughout this chapter describe in more detail how we believe the insurance market will be affected by the development of big data. In addition, we will discuss potential drawbacks and concerns of its use.

3.1 The Future of the Insurance Market

Deloitte Consulting LLP (Deloitte) has in collaboration with the World Economic Forum conducted a large study about the future of financial services. Their findings are summarized in the article "Five megatrends that will change financial services". They argue that changes in the insurance industry is driven by the same technologies that bring us the "connected lifestyle". New cars have sensors that make it possible to remotely collect information on every part of the vehicle. Devices that monitor and pick up risk factors are installed in homes of consumers. In addition, people have started to use wearable devices that track and store daily activity and behaviour. All these systems generate vast amounts of individual data which may be collected and analyzed by insurance companies to build better understanding of an individual's risk profile. This is one example on how we believe that big data will be used in the insurance industry. On a related note, much of this data comes in new and unconventional forms, allowing service providers to analyze new sides of their customers. Increasing connectivity in people's lives is therefore argued to enable more individualized insurance policies. Furthermore, insurance companies will have opportunities to use personal data to deliver value in other ways to customers. One example is that insurance companies will be able to use new sources of data to mitigate risk through individualized advice regarding customer behaviour (Deloitte, 2015).

Measurement of risk and pricing of insurance are traditionally based on a large, but limited amount of data. Often, simple criteria are used to categorize insurance takers into numerous groups. Insurance companies then use historical data to make an estimate of the future average risk of the respective group. The problem that arises is that individual risk varies within a group. This system therefore creates risk pools where high-risk individuals are cross-subsidized by low-risk individuals[4]. Now insurance companies have increasing opportunities to explore big data for more behavioural and contextual data regarding their customers‘ risk. Thus, insurance companies are expected to price individuals more accurately, reducing the problem of low-risk customers subsidizing high-risk customers.

Our belief is that using big data in the insurance industry will influence the traditional business model in many ways. However, in this paper we will mainly focus on how big data will allow for better risk classification of individuals and more personalizing of insurance policies, and the consequences of doing so. Other relevant aspects of using big data in the insurance industry will be included where we find it necessary.

3.1.1 Personalized Pricing of Insurance

To explain why insurance companies will benefit from using more data to better predict and price an individual's risk, we have to to understand why not doing so may cause problems.

[4]By cross-subsidization in an insurance setting, we refer to a situation where individuals have varying profitability which jointly make non-negative profits. An example is that individuals within a risk pool are priced the same, but have varying expected costs for the insurance companies. Those with lower expected costs than the average expected cost, are therefore said to be subsidizing those with higher expected costs. The relatively high-risk individuals are typically unprofitable for the insurance companies, but in combination with the profitability of the low-risk individuals, the overall profits may be equalized or even be positive.

Insurance products have different characteristics from other products sold in the consumer market. For the insurance companies, the marginal cost of providing insurance reflects their estimates of the expected loss of an insurance taker. For the insurance taker, the willingness to pay for insurance reflects her own beliefs regarding her expected loss. Due to information differences between the insurance companies and the insurance taker, there will often be differences in expectations. We are then in a situation with *asymmetric information*, meaning that one party in a transaction has more or better information than the other party. In an insurance setting it is normally assumed that the insurance takers have better information regarding their underlying risk than the insurance companies. This creates an imbalance of power in the transaction and may lead to market inefficiencies such as the problem of *adverse selection* and *moral hazard*. We will explain these problems more thoroughly in later chapters. For now we briefly discuss them in the context of big data and the opportunities to better predict an individual's risk.

The problem of adverse selection is related to the problem of cross-subsidization which we mentioned in the previous section. When individuals with different expected costs are offered the same insurance contract, the low risks will likely choose to underinsure themselves because they are priced too highly. Sometimes they will even choose to completely opt out of the insurance. The remaining insurance takers will then be an adverse selection of insurance takers with relatively high risk. As a consequence of information asymmetries and the difficulties in selecting customers, the insurance companies must typically raise premia or limit insurance coverage to reduce exposure to large claims. The problem of moral hazard is, on the other hand, related to unobservable characteristics of the insurance takers *after* they have entered into an insurance contract. The incentives for people to, for example, engage in risk preventive activities is often reduced after engaging in an insurance contract. This uncertainty of future behaviour typically poses problems for insurance companies when designing optimal insurance contracts.

Increased use of individual data and access to new sources of data in the insurance industry is argued to reduce both the problem of adverse selection and moral hazard. Both problems originate from asymmetry in information, and more knowledge about insurance takers will reduce this imbalance in information. For the insurance companies, this could for example mean that they will be able to serve new markets of low-risk individuals, which before had hard times finding fair prices for their insurance needs. In addition, pricing based on actual behaviour will more likely *increase*, rather than decrease, incentives for engaging in risk preventive activities after entering in an insurance contract.

3.1.2 Sensor Technology

Risk assessment based on sensor technology and monitoring of driving behaviour was first introduced in Norway by Rema Forsikring in 2016 (Rema 1000, 2016). If customers agree to their "drive smart" model, they will receive a 15% premium discount (Rema Forsikring, 2017). This requires an installation of a sensor in the car that monitors driving behaviour. The sensor monitors factors that Rema Forsikring claims statistically affect the risk of accidents, such as high speed, rough braking, high acceleration and what time of the day you are driving. Based on how you drive, you will receive a score which, in the case of responsible driving, will give additional bonuses when renewing the insurance the next year. Sparebank 1 Forsikring has also introduced a similar solution (Sparebank 1 Forsikring, 2017). It is also expected that several other insurance companies will follow their example. Tryg Forsikring has already stated that they will introduce a similar product called "Young Driver" to motivate young drivers to take up car insurance and drive more carefully (Bjørkeng, 2017).

Health insurance products that use sensor technology to monitor level of individual activity and health exist in the US and in some countries in Europe, but are currently not available in Norway. In the same way as with car insurance, "smart" health insurance rewards behaviour which reduces the probability of illness. In this way, the insurance taker can be rewarded with lower insurance premiums by sharing his exercise and health data. Moderna Försäkringar is a Swedish insurance company which gives their customers a discount based on the number of steps they walk. If they are able to walk between 7,500-9,500 steps on average each day, they will receive a discount between 5% and 15%

(Moderna Försäkringar, 2016).

The different types of insurance products mentioned in this section are not revolutionary in the sense that they dramatically change the way insurance is offered in the market, but they do give an indication on how insurance is transforming. There will be more information flow and interaction between the insurance companies and the insurance takers. Perhaps more importantly, the insurance premia will, in addition to more immutable characteristics, be dependent on actual behaviour of individuals.

3.2 Weaknesses of Big Data

Despite the advantages and possibilities regarding big data previously discussed, a more skeptical perspective may be appropriate as well. It should be stated that the usefulness of big data hinges on a model and the data that it utilizes. Thus, problems related to model-specification and/or data collected are of primary concern. First, problems related to overfitting may arise, in which out-of-sample prediction will be biased due to an incorrect weighting of the explanatory variables. On a related note, the model may be specified in ways such that correlations are interpreted as causation, which may lead to incorrect and/or unfair decisions. Further, mathematical models can be mistakenly designed to have a self-reinforcing pattern, meaning a misspecification may nevertheless be interpreted as correct over time, as the model picks out decisions without considering alternatives not implemented. This over time may then lead to a self-fulfilling prophecy type scenario.

Despite proposed advantages of basing decision-making on data analytics, there may be some fallacies that arise in the cross-section between data and decision making. Cathy O'Neil discusses in her paper "On Being a Data Skeptic" how we may get addicted to metrics and overly trust math due to its "hard" and "objective" nature. In reality, we may not be able to measure what we wish to assess, either due to the nature of what we are considering, or that our data-collection is skewed. In the case that we do have a measurement, it may not be a clean look at the phenomena we want to look at regardless. O'Neil warns us that we should understand that not everything is measurable, and that we should back up our quantitative analyses with qualitative insight (O'Neill, 2014). O'Neil goes on to discuss problems related to incorrect framing in models, wrong interpretation of proxies, and perverse incentives by consumers being observed. The perverse incentives related to observing individuals has been referred to as Goodhart's Law, which was originally formulated as follows: "Any observed statistical regularity will tend to collapse once pressure is placed upon it for control purposes" (Goodhart, 1984).

Related to data-issues will be the data that is collected and utilized. In calibrating a model, meaning has to be attached to the data that is used. The possibility of wrongly interpreting the meaning of a variable increases with the huge inflow of information that comes with big data. Attaching meaning to unstructured data, such as audio, video, imagery and unstructured text is relatively unknown territory, and we often rely on models to find use for these data. With data types that we are not used to attaching meaning to, we may be prone to seeing the data as having the most advantageous interpretation, while not being completely honest and calling a spade a spade.

Data-collection issues do not only concern what data is collected, but where it is collected from. Certain types of data might only be collected from a subgroup of people with characteristics correlated with variables of interest. If these characteristics are ignored when making general inference on a larger population, the interpretation is likely to be skewed. This is a case of what is known in econometrics as omitted variable bias, of which practitioners are wary of in order to infer causality. Our reason for bringing up issues like these is that data scientists in commercial sectors typically focus on prediction of variables, rather than causation. As such, despite firms reaching higher degrees of accuracy, they might be basing their accuracy on incorrect assumptions.

An underlying problem surrounding these issues, is the complicated nature of big-data models. In the case that a model fails for some consumers, wrongly classifying them, it may be difficult or nearly impossible to uncover these cases. The model may be deeply ingrained with huge amounts of data, and a human regulator would likely not be able to identify how the model has specified a categorization. Further, the incentive for a regulator would perhaps not be there to begin with, given that a model is correct most of the time, and the cost of uncovering outliers exceeds the companies' benefit of correctly classifying them. In that case, the responsibility to identify these misclasifications falls upon the misclassified targets themselves. These individuals may have the incentive to uncover their misclassification, but they may lack both the technical expertise to understand the big data model, as well as the data and information required to uncover the classification-decision. These victims of statistical discrimination, or "outliers", will be the ones most hurt by big data, and may yet be the hardest ones to help.

3.3 Redlining and Protected Classes

We take a moment to refer to a phenomenon that was, and to some degree, still is part of the financial services industry; redlining, or the act of limiting or refusing financial services to someone because they live in an area deemed to be a poor financial risk. Discussions on redlining have taken place primarily in the US and have been connected to debates on the causes of segregation and on forms of racial discrimination (Albers, 2011). The discrimination that arose from redlining would then be formed on either a statistical basis or on a basis of taste. The former could be justified to some extent from a business perspective if the overall risk in an area truly was poor. Concerns were raised with regards to equity, in the sense that some individuals' were refused services despite being eligible. The latter would refer to when providers of financial services were aware of the discrimination, but still carried it through due to some prejudice. The discussions regarding redlining have had major implications for policy, and regulations and laws have been put into place to ensure that people have equal access to services.

An example of a regulatory measure is that of ruling a class as "protected"; a protected class is a group of people with a common characteristic who are legally protected from discrimination on the basis of that characteristic (*Protected Class*, 2017). Laws pertaining to legal protection from employment discrimination have typically taken these protected classes into use. Protected classes have also been taken into use in insurance. In 2011 the European Union ruled that insurers in Europe will have to charge the same prices to women and men for the same insurance products without distinction on the grounds of sex, treading into effect at the end of 2012 (*EU rules on gender-neutral pricing in insurance industry enter into force*, 2012). Whether sex should be a protected class is disputed, as it has been proven that men and women are heterogeneous in risks in different insurance types. A report from Statistics Norway shows that life expectancy was approximately 84 years for women and 80 years for men in 2015 (Statistics Norway, 2016). In other words, men are more likely than women to die younger. On the other hand, women are more likely to receive disability benefits. Statistics from NAV shows that 58,1% of recipients of disability benefits are women per September 2017 (NAV, 2017). It is argued that using sex as a variable in risk assessment will lead to more correct pricing. On the other hand, there may be normative reasons to not discriminate based on gender.

It varies as to what characteristics are protected, both geographically and across lines of insurance, but typically discussed classes in these settings are race, national origin, religion, gender, age, credit score, genetics, sexual orientation, and zip code, as was compiled in a database by Avraham, Logue, and Schwarcz (2013). Common for these are that there is some normative agreement that they should not be used to discriminate. There is seldom a justified logic in claiming a causal relationship between a protected class and risk, despite correlations possibly existing. Despite the existence of a correlation, we likely find normative reason to claim that we should not take these into use.

Despite these efforts made, discrimination still happens, whether it is statistically based or taste-based. Some companies may bypass regulations, and find ways to increase profits despite the injustices that may arise.

We want to note a reflection on the role big data may play in all this. As we have argued, big data may enable firms to predict and estimate with precision unlike what we have seen earlier. We then pose the possibility for firms to bypass regulations that prohibit discrimination through proxies. A simple example would be that a big-data model could effectively simulate gender by analyzing activity and consumption bundles of an individual, or simulating race by using home addresses or postal codes if these are correlated. Some of these approximations are fairly easy to uncover, and can be dealt with by a judiciary body, while some may be very difficult to observe, as they may be based on a multitude of variables. Related to big data, is the use of artificial intelligence, which in one study was used to create an artificial intelligence (AI) that guessed the sexual orientation of persons based on facial images with much higher accuracy then human judges (Wang & Kosinski, in press). Though not necessarily directly relevant, this shows that firms may be able to estimate and predict factors that we have till now deemed impossible. If these factors are used, and kept in the dark, we may see a new age of redlining and discrimination, based not on geography, but digitalism.

3.4 Privacy Concerns

Another issue of using more personal information in an insurance setting is the privacy concerns of individuals. In November and December 2016 the Norwegian Data Protection Authority conducted a privacy survey. They asked 1,001 Norwegians about their attitudes towards the use of personal data in the financial sector and the public sector. The survey illustrates, among other things, Norwegians' acceptance of new insurance models, how they value their privacy, and their willingness to share information about themselves to receive personalized services (Data Protection Authority, 2017).

The main result is that there is a general skepticism regarding the use of private information by insurance companies. The survey found that 69% of respondents were negative to a development where insurance premiums are calculated on the basis of detailed sensor-generated data about their day-to-day lives and behaviour. Only 12% were positive. However, if the respondents were told that insurance schemes based on personal behaviour resulted in significantly reduced premiums, the share of negative respondents decreased to 63%. It is worth noting that those over the age of 50 were more negative than those under the age of 30 in both scenarios.

The survey also indicated that Norwegians are less willing to give away data on personal health and physical activity than they are of giving away data on for example personal driving behaviour. In health- and life-insurance only 16% agreed (and 63% disagreed) that they wanted health- and life-insurance premiums to be calculated from health-related sensor data. On the other hand, in car insurance, 39% agreed (and 38% disagreed) that they wanted car insurance premiums to be calculated from actual driving behaviour.

As previously discussed, using big data to monitor individuals and their behavior will ultimately allow insurance companies to play an increasingly active role in their lives. This could for example be for insurance companies to actively encourage individuals to reduce their risk of illness by engaging in more physical activity. In this way, using big data could reduce "bad" behaviour and the problem of moral hazard. The survey indicates that there are some barriers that insurance companies need to overcome if they wish to play a more active role. In health- and life-insurance only 10% agreed (72% disagreed) that they want their insurance company to actively interfere with their health. On the other hand, Norwegian consumers seem relatively open to government usage of private data in the health care sector and in research.

3.5 The New Privacy Regulation (GDPR)

We have till now discussed possibilities, issues and concerns that may arise in connection to the development of big data. A call for regulation may be in order, and we briefly describe a major development occurring in Norway.

The new privacy regulation (General Data Protection Regulation, GDPR) will take effect in the EU and Norway in May 2018 (Data Protection Authority, 2017). The increasing amount of personal information stored digitally is argued to be one of the main drivers for more regulation. The new regulation will strengthen individual control of personal information as well as forcing businesses to use data more responsibly.

As a result of the new regulation, Norwegians will be given new rights such as: 1) The right to demand that personal data is deleted, 2) The right to have data portability between businesses, and 3) The right to oppose profiling and automatic decisions based on personal information. Businesses will, among several things, be imposed to have an understandable privacy policy as well as implementing *privacy by design*. This means that the systems which handle personal information should be sufficiently secured in order to avoid unauthorized access, sharing, changing or destruction of personal information. Businesses violating the new privacy regulations will in addition be charged fines up to 4 percent of annual turnover; a substantial increase in comparison to current regulation.

There is no doubt that some of the aspects of the new regulation will potentially be very costly for some businesses to implement, and the new regulation will therefore encounter some resistance. However, Lars Erik Fjørtoft, partner in PwC, claims that the new regulation will make it easier and safer for individuals to offer their personal information to businesses in order to receive personalized services and benefits (Fjørtoft, 2017). He argues that the GDPR will therefore increase the opportunities for businesses to collect valuable information about their customers, and that the focus on privacy should no longer be considered only as a cost, but rather as a potential source of income.

The financial sector is said to be well prepared for changes that comes with the GDPR (Finance Norway, 2017). The banking and insurance sector have access to large amounts of various sensitive information regarding their customers, relevant for loan- and insurance-applications etc. To ensure an efficient privacy policy, the financial sector has already implemented a strict regime for processing customer information. In terms of better access to valuable customer information, the new regulation is therefore more likely to be valuable for the insurance sector.

4 Literature Review

In this chapter, we review literature we find relevant for our research question. We begin by introducing traditional issues that have been discussed in the insurance literature, namely those of asymmetric information. We then go on to discuss categorization, how it alleviates the aforementioned problems, as well as issues related to categorization when it is based on imperfect signals.

4.1 Asymmetric Information - Adverse Selection

Much of prior research within insurance surrounds the concept of asymmetric information. In the case in which both suppliers and insurance takers are fully and symmetrically informed, insurance takers will be categorized and offered a contract that perfectly reflects their expected cost, given a competitive insurance market. Things get more complicated when we introduce an asymmetry of information, meaning that insurance takers have better information regarding their underlying risk than the insurance companies.

The literature surrounding asymmetric information mainly considers two types of asymmetric information; adverse selection and moral hazard, in which the latter will be described in the subsequent section. The former refers on a very general level to when one party has a better information than other parties about some parameters that are relevant for the relationship. The part with the better private information surrounding the relationship will selectively participate in trades which benefit them the most, at the expense of the counterpart. Knowing this, the uninformed part may choose not to engage in a contract at all. A textbook example of this setting is Akerlof's market for lemons (Akerlof, 1980). In an insurance setting, it is typically assumed that the insured has better information than the insurance companies regarding her accident probability and/or on the (conditional) distribution of losses incurred in case of an accident. The insurance taker's informational advantage relates to knowledge regarding her risk, which directly impacts the insurer's expected costs (Chiappori & Salanié, 2013).

In modelling insurance markets, a seminal paper was written by Rothschild and Stiglitz (1976), in which insurance companies were modelled to offer contracts specifying both premium and amount of indemnity in a setting with asymmetric information. A year later, Wilson (1977), made a similar contribution, but in which he specifies an equlibrium in cases in which Rothschild and Stiglitz state one may not exist. The main findings in these papers are that low risks will either become underinsured or will subsidize insurance takers of higher risk in equilibrium. These results will be explained in depth in the theory chapter later, as they are utilized in our own modelling of an insurance market.

4.2 Asymmetric Information - Moral Hazard

Moral Hazard occurs when the probability of a claim is not exogenous, but depends on some decision made by the subscriber. This decision will typically be some type of accident prevention. Given that this action is observable and contractible, an optimal decision (i.e. most preventative) will typically be part of the insurance contract. However, when the decision is not observable or verifiable, there may be a weakened incentive for the insured to reduce risk ex post of engaging in the insurance contract (Chiappori & Salanié, 2013). For example, an individual with high coverage in his car insurance, may feel less obliged to drive safely than he did before being insured. This asymmetry in an individuals risk profile before and after signing up for insurance poses problems for insurers in calculating optimal insurance contracts.

Holmström (1979) presents a model in which an agent (in insurance: the insurance taker) may engage in a private action that affects the probability distribution of an outcome (an accident). Pareto-optimal risk sharing is generally precluded, as it will not induce proper incentives for accident-prevention. There may, as mentioned, be cases in which monitoring of the insured is possible and with low costs, yielding an optimal allocation of insurance. However, when such a monitoring is impossible or very costly, a second-best solution can be achieved by trading off some coverage for provision of incentives. In an insurance-setting, this is seen as adding a deductible to the contract, so that the benefit of acting in a risky behaviour is off-set by a cost.

The use of big data and increased connectivity is one way in which we expect problems of moral hazard to be alleviated, due to the monitoring aspects present. Analyses of how this may affect different types of insurance takers may be in order, but we will not do this in this thesis.

4.3 Categorization

We have described the main problems related to a market in which asymmetric information is present. We turn our attention to the possibility for insurance companies to reduce the problem of adverse selection by categorizing insurance takers into risk pools; if an insurance company is able to identify signals or characteristics which are correlated with an individual's risk, it may use these variables to create several risk pools, in which differences between individual risks is smaller.

The efficiency and equity effects of risk categorization in insurance markets have been a source of substantial debate. The primary concerns have been the adverse equity consequences for individuals who are categorized unfavourably, and the extent to which risk categorization enhances efficiency in insurance contracting. A general consensus is that, for insurance markets with asymmetric information, risk categorization enhances efficiency. Categorization based on observable characteristics or behaviour statistically correlated with riskiness, provides insurance companies with more information about the insurance takers which mitigates adverse selection inefficency (Crocker & Snow, 2000). Furthermore, market forces typically push insurance companies to engage in risk categorization as long as the marginal cost of more categorization is not too large. The intuition is simple; by uncovering groups of lower risk and offering lower-priced insurance products, insurance companies will be able to attract the most profitable risks. For other companies to avoid large claims from the remaining high risks, they will either have to increase premia and serve only the high risks, or engage in similar risk categorization as well.

In the discussion to follow in this section we will highlight some of the consequences for individuals who are categorized unfavourably or wrongly. In an assessment of risk, the information that firms observe is likely to be imperfectly correlated with underlying risk. We consider this to be the case as we discuss two types of categorization and the implications they bear; exogenous and endogenous risk indicators. Common for these factors will be that they need to be correlated with risk, as well as observable.

4.3.1 Exogenous Categorization of Risk

By exogenous categorization, we refer to the case in which a firm categorizes an individual based on immutable (meaning the insured is not able to affect her status) and observable characteristics that are specific to her. Common examples of exogenous factors are sex, age and race.

Insurance companies' use of immutable and observable characteristics to categorize individuals raises several equity issues. One proposed way to measure equity differences is by means of price discrimination. The standard view of price discrimination implies that prices should reflect differences in expected costs of insurance takers and this suggests that the initial cross-subsidization based on no information and no categorization is unfair. Schmalensee (1984) assesses the market for automobile insurance and presents a model where total aggregate price discrimination is the sum of vertical price discrimination (those who are unequal in terms of risk should be priced in ways that "fairly" reflect their differences) and horizontal price discrimination (those with equal risk should be priced equally). The essence of the analysis in this paper stems from the fact that, although using a more informative (yet not perfect) signal to assign individuals to their true risk classes improves the accuracy of the assignments, it also means that those who are misclassified face a greater price-cost differential in insurance. Schmalensee finds that better information generally reduces both total aggregated discrimination and vertical discrimination, but it may well increase horizontal discrimination. Improvements in information are more likely to reduce horizontal discrimination, the more substantial the improvement and the better the initial information (Schmalensee, 1984).

Hoy and Lambert (2000) assess the use of genetic screening tests to determine the price of health insurance and present a similiar model as the one from Schmalensee. In their paper they conclude that using information from geno-type tests to set insurance premiums leads to more, rather than less, aggregate price discrimination. The reasons for this conclusion revolve around the realities associated with genetic diseases as well as compelling normative concerns[5]. Even very accurate genetic tests, which lead to a small fraction of individuals being misclassified, can generate substantial horizontal discrimination within either risk class due to the significant differences in the costs of insurance provision (Hoy & Lambert, 2000).

4.3.2 Endogenous Categorization of Risk

We here consider factors related to risk that the insurance takers may affect. In contrast to categorizing based on immutable characteristics, the insurance takers here will have a say in how their premia are calculated. Typically, firms have considered the actuarial relationship between consumption of correlative products and underlying risk, which permits insurers to design contracts that mitigate problems of moral hazard and adverse selection related to asymmetric information (Crocker & Snow, 2000). Another source of endogenous categorization are the insurance takers' choice of actions that are not priced in the market; for example the number of steps taken by an individual per day. These health-promoting actions, if insurance companies are allowed to observe them, can then be used in a risk assessment.

Bond and Crocker (1991) analyze the efficiency and equilibrium effects of endogeneous categorization, and show that categorization based on insurance takers' voluntary consumption of correlative products may permit the attainment of efficient allocations as

[5]From a normative perspective, it is argued to be of interest to place more concern on the dispersion in price-cost ratios between individuals for whom the levels of those ratios are higher. The reason for doing so is that those with the highest price-cost ratios resulting from imperfect categorization are those who are most heavily discriminated against.

competitive Nash equilibria. They show that modest problems of adverse selection may be self-correcting if insurers are permitted to engage in endogenous categorization, assuming consumption of a hazardous good increases the probability of a loss[6] (Bond & Crocker, 1991). In their model, they assume that the probability of a loss has a direct link with the consumption of a hazardous good. We pose that such links may be plausible for many signals, but pose that there may be instances in which signals are imperfect, meaning that they do not correlate with risk for all individuals.

5 Theory

In the following we present theory that we later apply in our methodology, and will refer back to this chapter in our analysis. We limit our analysis to the problem of adverse selection.

5.1 Asymmetric Information - Adverse Selection

As we have discussed in our literature review, much of the research on asymmetric information in insurance bases itself on Rothschild and Stiglitz (1976) and Wilson (1977). We present an insurance setting in the style of these, and derive equilibrium concepts that will be later used in our own analysis of the insurance market. Rees and Wambach (2008) provide an overview of the theory of insurance, which we also take into use when describing our theoretical framework.

5.1.1 The Market for Insurance

Insurance Contracts: We consider a setting with individuals who will have an outcome that can take one of two values, contingent on whether an accident occurs or not. Denoted

[6] Bond and Crocker note that the relationship may be the consequence of a direct causal link, or merely a statistical relationship, both of which provide interesting information to insurance companies.

as a measure in wealth, it takes the size $W_1 = W$ if they are not afflicted by an accident. In the event of an accident, wealth will be $W_2 = W - D$, where D is interpreted as a loss. An individual is able to insure himself against this affliction by paying a premium α for which he is compensated with an indemnity β (also referred to as coverage) if an accident occurs. Thus we can say that a vector, $\omega = (\alpha, \beta)$, completely describes an insurance contract. We assume that individuals buy only one contract with only one insurance company. If an individual is insured, her wealth in the respective states is $W_1 = W - \alpha$ and $W_2 = W - D - \alpha + \beta$.

Demand for Insurance contracts: We assume that all insurance takers are identical in every way, save for their probability of incurring a loss. For simplicity, we consider two types only: Low risks (l) and high risks (h). We set the probability of losing D as $p^i, i = l, h$ where $p^l < p^h$. The share of low risks in the society is denoted by τ, and the remaining share of high risks is $1 - \tau$. The average risk in society is therefore: $\bar{p} = \tau p^l + (1 - \tau)p^h$. This is the probability that a randomly drawn insurance taker will incur a loss. We assume that all consumers have the same utility function $U(\cdot)$ which is defined over all nonnegative values of wealth. Further, $U(\cdot)$ is assumed strictly increasing, strictly concave and twice differentiable from R_+ to R, implying well-behaved risk aversion, as discussed in the section for Demand for Insurance (2.2.1). If insurance contracts are traded on a market, an individual will purchase a contract to alter her pattern of income across the states of nature, yielding W_1 or W_2. The expected utility theorem[7] states that the preferences for income of an individual of type i are described by the following form:

$$\hat{V}^i(p^i, W_1, W_2) = (1 - p^i)U(W_1) + p^i U(W_2)$$

Totally differentiating the expected utility, holding utility constant and rearranging, yields the slope of an individual's indifference curve:

[7]The theorem states that under a set of axioms, the choice of an individual under uncertainty can be expressed as a maximization of the expectation of a utility function. These axioms are completeness, transitivity, continuity and independence. For an explanation of these axioms see: Machina and Viscusi (2014).

$$0 = (1-p^i)U'(W_1)dW_1 + p^i U'(W_2)dW_2$$
$$\rightarrow -\frac{dW_2}{dW_1} = \frac{1-p^i}{p^i}\frac{U'(W_1)}{U'(W_2)} = MRS^i$$

With W_1 on the horizontal axis and W_2 on the vertical axis, we see that an indifference curve for a low-risk individual will be steeper than for the high risks. If one considers the case in which wealth is equal in both states ($W_1 = W_2$), then the slope of the indifference curve will be $(1-p^i)/p^i$.

Note that since the only source of heterogeneity is the probability of loss, our set of indifference curves will have a single crossing property, meaning that for all levels of insurance, $MRS^l > MRS^h$. This property is crucial for the following analysis and implies that the indifference curves cross once only. Note that if individuals differ in their wealth or some other characteristics in addition to their risks, then the single crossing property may be violated.

Supply of Insurance: We now turn to the supply-side of the insurance market. We first note that the return from an insurance contract $\omega = (\alpha, \beta)$ will be a random variable, based on the probability of loss. The insurer cannot observe an individual's risk, but knows the share of high risks and the share of low risks in society. We assume risk-neutrality for insurance companies and that they behave as expected-profit maximizers[8], and we limit our analysis to competitive insurance markets[9]. The value of a contract is given as:

$$\pi(p^i, \omega) = (1-p^i)\underbrace{\alpha}_{\substack{\text{Profit w/o}\\ \text{accident}}} + p^i \underbrace{(\alpha - \beta)}_{\substack{\text{Profit w/}\\ \text{accident}}}$$

Where α is the profit of a contract in the lucky state (i.e. no accident), and $\alpha - \beta$ is the

[8] Rothschild and Stiglitz argue that even in the case in which firms are not expected-profit maximizers, they will behave as such if the market is well-organized and competitive.

[9] Monopolistic competition with non-linear contracts is analyzed in a paper by Stiglitz (1977), where it is shown that low-risk individuals are underinsured, and may not purchase insurance at all, while high-risk individuals always purchase full insurance.

profit in the unlucky state.

5.1.2 Linear Insurance Contracts

We start off this section with insurance contracts which specify only premia, meaning that insurance takers can, given a premium, purchase whatever amount of indemnity they want. This implies that given a price, and an expected-utility maximizing individual, we can uncover a linear relationship between indemnity purchased and price set.

On the two axes in figure 2 are wealth in the two states (lucky state, unlucky state), and point $E = (W, W - D)$ describes the initial endowment without insurance. The security line (S) illustrates full insurance, i.e. when the expected wealth in each state is equal ($W_1 = W_2$). The lines $\overline{Eh}$ and $\overline{El}$ are the zero-profit lines for each type, which have the slope $(1-p^i)/p^i$ for $i = l, h$[10]. An insurance contract for risk type i below (above) the zero-profit line for risk type i will be profitable (unprofitable) for the insurance company. In other words, if an insurance contract lies between the lines $\overline{Eh}$ and $\overline{El}$, it will be profitable for the insurance company if the low risks purchase it, but it will be unprofitable if the high risks purchase it. $\bar{U}^h$ and $\bar{U}^l$ denote the indifference curves for the high risks and the low risks, respectively.

Consider an insurance contract with a fair pooled premium across risk types, $\bar{\alpha} = \bar{p}\beta$, in exchange for an insurance indemnity equal to β. Amount of indemnity available for purchase is by definition not regulated by the insurance companies. The fair pooled premium contract line ($\overline{EP}$) will have the slope $(1 - \bar{p})/\bar{p}$ and lie between the two zero-profit lines in figure 2. Now the high risks will have incentives to overinsure themselves (point ω^h) while the low risks will underinsure themselves (point ω^l). Earlier it was shown that along the security line ($W_1 = W_2$), the slope of the indifference curves is $(1 - p^i)/p^i$. Therefore, the high-risk (low-risk) indifference curve will be tangential to

[10]The zero-profit condition for insurance companies yields $\pi = (1-p^i)\alpha + p^i(\alpha - \beta) = 0$. Differentiation and rearranging yields $-\frac{d(\alpha-\beta)}{d(\alpha)} = \frac{(1-p^i)}{p^i}$

the pooled contract line to the left (right) of the security line[11]. Due to this over- and under-insurance, a fair pooled premium will lead to negative profits for the insurance companies. For profits made with low-risk types to offset losses made with high-risk types, they must buy the same contract on the pooled contract line. Thus, there are two inefficiencies arising: First, individuals do not buy the efficient amount of insurance. Second, prices have to be larger than the fair pooled premium to avoid losses for the insurer. Governmental intervention, e.g., by obliging everyone to buy full insurance at the fair average premium is one way to eliminate the inefficiencies. In this case both types will place themselves in point ω^G, where the pooled contract line crosses the security line. It is worth noting that both risk types are worse off by this intervention, relative to their optimal allocations. However, if we do not allow for an intervention in a common coverage level, the insurance market may fall apart due to negative profits.

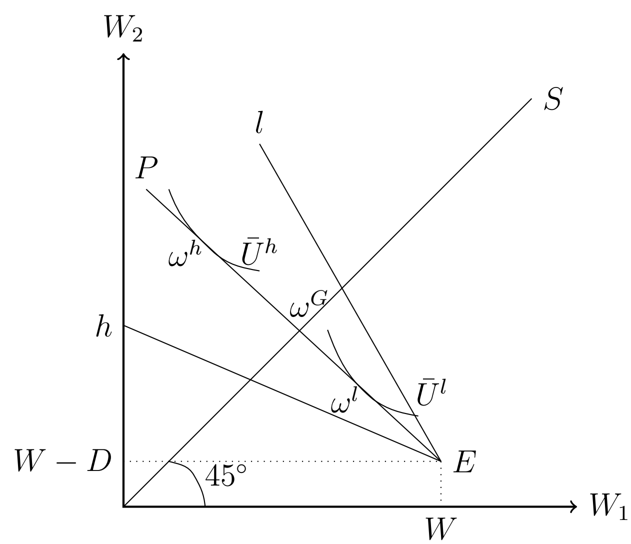


Figure 2: Asymmetric information: Linear Insurance Contracts

[11]In the point where the pooled contract line crosses the security line, the following holds: $(1-p^h)/p^h < (1-\bar{p})/\bar{p} < (1-p^l)/p^l$. The high risks will therefore increase their utility by purchasing more than full insurance ($\beta > D$) along the pooling contract line, and the low risks will increase their utility by purchasing less than full insurance ($\beta < D$) along the pooling contract line.

5.1.3 Non-linear Insurance Contracts

We have so far limited our analysis by assuming insurance companies set only a price for their insurance policy. Rothschild and Stiglitz (1976) and Wilson (1977) contributed to the literature by modelling insurance contracts as menus of premia and indemnity as a reaction to asymmetric information. These contract sets can thus be interpreted as being non-linear, in the sense that there is not necessarily a linear relation between premia and indemnities in the contracts traded. The insurance companies attempt to set combinations of premia and indemnities that maximize expected profits under asymmetric information. Rothschild and Stiglitz show in their seminal paper that only a separating equilibrium may arise, meaning different risk types will receive different offers. The insurance company makes its menu of contracts available in a way that makes the insurance takers reveal their type. An assumption is that individuals buy only one contract with only one insurance company. Further, Rothschild and Stiglitz find that there may be cases in which an equilibrium does not exist. Wilson contributes to the literature, and shows that in these cases there might exist a pooling equilibrium in which everyone purchases the same contract.

Rothschild & Stiglitz (RS) - Equilibrium

As before, the point of departure is the initial state ($E = (W, W - D)$), which describes the initial endowment without insurance. Depicted in figure 3 are the zero-profit lines for each type (with slopes $(1 - p^i)/p^i, i = l, h$), as well as a pooling zero-profit line with a slope $(1 - \bar{p})/\bar{p}$. We also map out indifference curves for each type, with the low-risk having a steeper slope. As we assume a competitive market with identical providers of insurance, we expect zero profits to be made on average.

As a benchmark we can consider the case of *symmetric information.* In this case, both types of consumers would fully insure themselves, yielding the set of contracts $(\omega^h, \hat{\omega}^l)$ depicted in figure 3. As such, the providers of insurance actively discern each consumer's type and offers her the actuarially fair contract. The marginal rate of substitution is equal to the slope of the contract lines for each types when the consumers are fully insured ($W_1 = W_2$). The insurance companies will be incentivized through competition to offer the best possible set of contracts that yield a nonnegative profit, so that utility for consumers is maximized along the zero-profit line of each type. Under the assumption of risk aversion for insurance takers, an individual will choose a certain amount over a lottery with the same expected value. Thus, given actuarially fair prices, an insurance taker will choose full insurance yielding equal wealth in both states without reducing the expected value of her wealth.

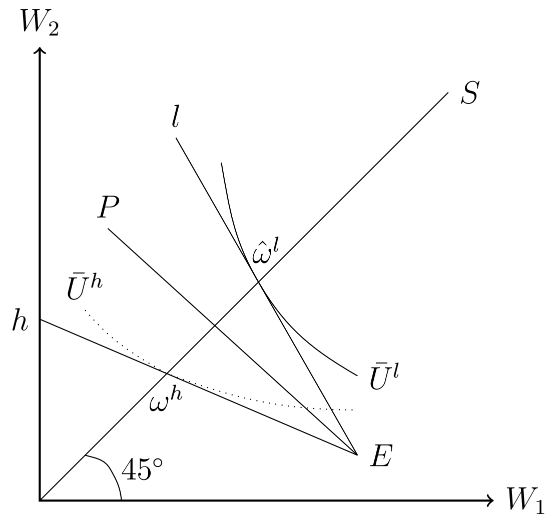


Figure 3: Symmetric information: Full insurance at fair premium for both risk types

Under *asymmetric information*, where firms are unable to discern an individual's type, they are disabled from granting tailored contracts. Thus, they must offer a set of contracts available to everyone. We see that the contract set $(\omega^h, \hat{\omega}^l)$ will yield negative profits, as both types will choose to buy the low-risk's contract $\hat{\omega}^l$, and the companies will on average lose on the high risks given this price. With this, the insurance companies are left to either offer a pooling contract that both types purchase, or a set of contracts that incentivizes self-selection. We must then assess if either of these will constitute an equilibrium.

We can first assess whether a pooling contract may be an equilibrium. First of all, a pooling contract below the pooling zero-profit line $\overline{EP}$ will give positive profits for the insurance companies. This can not be an equilibrium in a competitive market; if profits are positive then there is a different contract that offers slightly more consumption in each state of nature, which still will make a profit when all individuals buy it. Thus, if there is to exist an equilibrium it must be located on the pooling zero-profit line. Consider therefore any contract ω^P on the pooling zero-profit line $\overline{EP}$, depicted in figure 4. Now assume the effects of one firm offering a contract a that lies above the low-risks' indifference curve and below the high-risks' curve. This new contract will be attractive only to the low risks, and will make positive profits. As the low risks opt out of the pooling contract, it will become unprofitable. This simple argument establishes that a pooling contract cannot constitute an equilibrium.

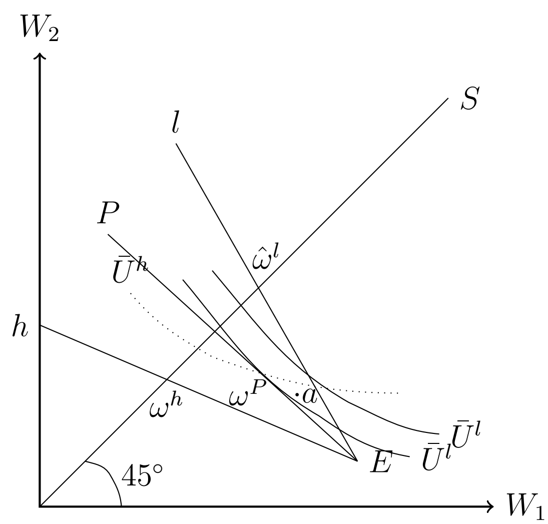


Figure 4: Asymmetric information: Pooling equilibrium does not exist

We then turn to consider whether a separating contract may constitute an equilibrium, in which each type self-selects. We can by similar argumentation as with the pooling contract, establish that in a separating equilibrium, each contract type must make zero profits in expectations, meaning there is no cross-subsidization. This means that the high-risks' contract must lie on the high risk zero-profit line ($\overline{Eh}$). The high risks will be offered full insurance through the contract ω^h in an equilibrium, as they will always have the option of admitting that they are of high risk, and should thus receive their actuarially fair contract. The low risks cannot be offered more coverage than to the point where the high-risks' indifference curve through ω^h crosses the low risk zero-profit line ($\overline{El}$), yielding the contract ω^l, as depicted in figure 5. Competition will push each firm to offer these contracts, and given static expectations regarding competitors' actions, this constitutes a separating equilibrium (ω^h, ω^l) of the Cournot-Nash type[12]; each firm assumes that the contracts its competitors offer are independent of its own actions.

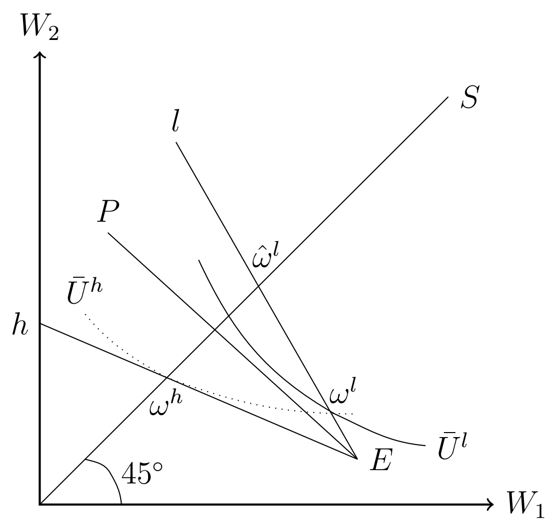


Figure 5: Asymmetric information: Separating equilibrium exists

It should be noted that in the framework described, there may be cases in which the separating equilibrium does not exist. For there to be an equilibrium the share of high risks need to be sufficiently large. Suppose a firm offers the separating contract (ω^h, ω^l), as depicted in figure 6. We see that if another firm was to offer a pooling contract that lies above both types' indifference curves that crosses ω^l and below the pooling zero-profit

[12]The RS definition of equilibrium in insurance markets is equivalent to Nash's equilibrium of the following game: At stage one, risk-neutral firms offer one contract each. At stage two, customers choose between contracts. The argument that the insurance companies specifies both the prices and quantities of insurance purchased, depends heavily on the assumption that price and quantity competition (Cournot), and not simply price competition (Bertrand), characterizes the competitive insurance market. Rothschild and Stiglitz argue that price and quantity competition can dominate price competition; if the market is in equilibrium under price competition, a firm can offer a contract, specifying price and quantity, that will attract the low-risk customers away from the companies offering contracts specifying price alone. Left only with high-risk customers these firms will lose money. This argument hinges on one crucial assumption: regardless of the form of competition, customers purchase but a single insurance contract (Rothschild & Stiglitz, 1976).

line, the contract will make a strictly positive profit. One such contract may be the contract a. The pooling contract will attract both types of customers, but as we have shown, a pooling contract cannot be an equilibrium. The setting which brings about the nonexistence of an equilibrium is when the pooling zero-profit line is sufficiently close to the low-risks' zero-profit line ($\overline{EP}$ is sufficiently close to $\overline{El}$). In other words, when there is a relatively small share of high-risk individuals in the market.

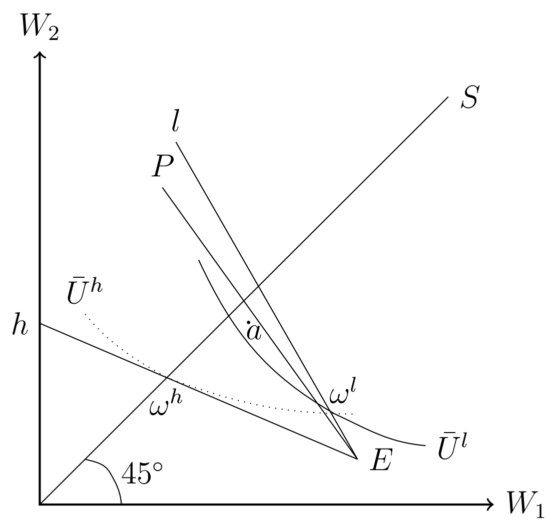


Figure 6: Asymmetric information: No equilibrium exists

Wilson E2 Equilibrium

The potential nonexistence of an equilibrium in a competitive insurance market poses problems for our analyses of insurance markets. Rothschild and Stiglitz do not find an intuitive explanation to the nonexistence, and the non-existence of an equilibrium in pure strategies of the Rothschild–Stiglitz model is still a problem in the insurance literature. This equilibrium non-existence debate is relevant, as adverse selection has quite often been brought forward as an argument for governmental intervention in insurance markets (Rees & Wambach, 2008). If the share of high-risk individuals is low, there will exist a pooling contract which both types of consumers will prefer to the RS separating contracts, but it cannot be an equilibrium in the RS framework due to cream-skimming incentives for insurance companies[13]. On the other hand, rather than using this as a reason to call for governmental intervention one might interpret the equilibrium non-existence as a sign that the RS model is not fully capturing what is going on in the insurance market when there are just a few high risks.

As such, we may need to modify our analysis. Rees and Wambach (2008) provide an overview of contributions to the literature in solving the nonexistence problem. We find that one of the most appropriate ways of ensuring the existence of an equilibrium is by modifying the equilibrium concept, as first done by Wilson (1977). This is equivalent to revising the expectations of the competing insurance companies. He states that a set of policies is an E2 equilibrium[14] if each policy earns nonnegative profits and there is no other set of policies which earn positive profits in the aggregate and nonnegative profits individually, after the unprofitable policies in the original set have been withdrawn. This means that the firms considering offering a new contract take into account the effect the new offer has on the profits of existing policies. Using this concept, we see that a pooling contract may be an equilibrium, as firms will foresee the eventual unprofitability of offering a contract that attracts only low risks, as high risks will follow suit after the pooling contract is unravelled. Thus, with competition, and the absence of an RS-equilibrium, a pooling contract offered at point where the low-risk indifference curve ($\bar{U}^l$) is tangent to the pooled zero-profit line ($\overline{EP}$) will be a Wilson E2-Equilibrium[15], yielding partial insurance to both types. This equilibrium can be seen in figure 7 as ω^P. In the pooling-contract equilibrium, low-risk types will to some degree subsidize the high-risk types.

[13]Cream-skimming is a term used when insurance companies provides insurance only to the low-risk individuals, while disregarding high-risk individuals that are less profitable

[14]In the original paper by Wilson, the Wilson E1 equilibrium corresponds to a RS equilibrium in separating contracts. As such, we do not go in depth to discuss E1 equilibria before considering the E2 type. Further, it can be shown that an E1 equilibrium also will be an E2 equilibrium.

[15]We should note a potential limitation with the Wilson E2 equilibrium. There may be compositions of consumers that bring about cases in which a unique E2 equilibrium does not exist; that is, we may have multiple E2 equilibria. Wilson does not find general conditions under which the E2 equilibrium is unique. In our analysis, this does not appear to be the case, and the E2 equilibrium is applied in the cases in which an RS-equilibrium does not exist.

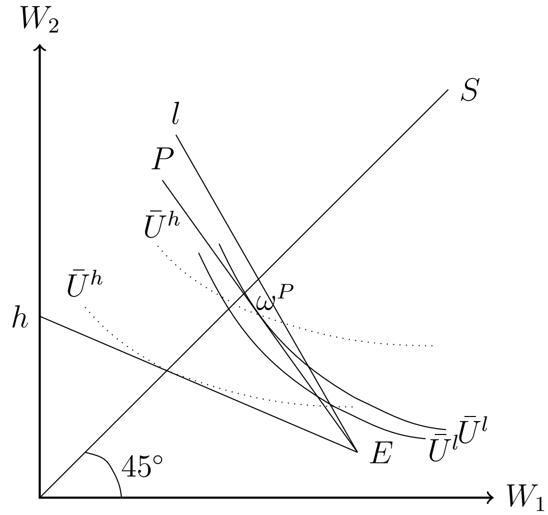


Figure 7: Asymmetric information: Pooling equilibrium exists

With this, we have provided notions of equilibria that will prove useful in our analysis of the insurance market. We now go on to provide a basis for which we can assess the various equilibrium outcomes that arise in our analysis.

5.2 Discrimination, Pareto Efficiency and Kaldor-Hicks Efficiency

In our paper, we are interested in understanding how low-SES individuals are affected by the use of big data. Further, we need to consider economic consequences at a more aggregate level, both in order to make normative judgment as well as to understand the underlying motivation for utilizing big data. An underlying assumption is that big data will bring along some type of efficiency gain, while we are interested in understanding how different groups are affected by this transformation. In the following, we provide an overview of concepts surrounding efficiency, discrimination and the interplay between the two.

5.2.1 Pareto Efficiency

Familiar to any student of economics, is the concept of a pareto improvement, embodying an idea of non-wastefulness in allocations of goods. Given an allocation, if it is possible to reallocate goods as to make at least one person happier and no one worse off, then the original allocation is wasteful in the sense that there is room for improvement (Banerjee, 2015). The possible reallocation is then considered a pareto improvement. In our setting, we consider allocations of insurance coverage given premium levels, and assess whether reallocations given the implementation of big data can be viewed as pareto improvements. In other words, we consider whether only winners emerge from the change brought about by big data.

5.2.2 Kaldor-Hicks Efficiency

Despite the objective nature of pareto efficiency, in which no pareto improvements can be made, it is often of limited usefulness in welfare considerations. Most changes in the economic climate bring about both winners and losers. As such, it is of interest to be able to make inference even in these cases. Hicks (1939) and Kaldor (1939) developed the *compensation criterion*, which bears their names. If a development brings about winners and losers, and the winners have the theoretical possibility of compensating the losers while still being left better off, this development should be considered economically attractive. Note that the political question of whether a compensation is carried out is left out of the definition. However, in the case of the compensation being brought about, bringing everyone as well off as before and some better off, this is then a pareto improvement, and will be unanimously supported (Newman, 1998).

5.2.3 Discrimination

In understanding adverse effects that certain groups face, a key concept is that of discrimination. There are two related, but distinct concepts that we need to describe; what we refer to as price differentiation, based on risk categorization, and that of discrimination, based on irrelevant characteristics. The former is an economic concept in which differences in prices should reflect differences in expected costs. In a market with heterogeneous consumers, where expected costs of insuring an individual are dependent on her risk profile, prices that are deemed actuarially fair will reflect a specific individual's risk assessment. In this sense, price differentiation is justified in the standard economic view of price discrimination. There may however exist fairness considerations in a pricing scheme that need to be considered normatively.

For the latter way in which we consider discrimination, we can define it as a distinction in favor of or against a person on the basis of the group, class, or category to which the person or thing belongs rather than according to actual merit. As such, if we find that an individual faces a price that does not correspond to her expected costs due to some belonging that is irrelevant to her risk profile, she faces discrimination. This form of discrimination is considered to be unanimously undesirable. We note that there may be cases in which discrimination may be considered as a redistributive tool, and thus desirable. Whether discrimination is to the advantage or disadvantage of an individual, it can be modelled as a price deviating from an actuarially fair price. Seeing this deviation relative to the actuarially fair price, we can use the ratio between actual price (α) and actuarially fair price (α^*) as a measure of discrimination:

$$\frac{\alpha}{\alpha^*}$$

We can then interpret negative discrimination as a ratio higher than 1, and negative discrimination as a ratio lower than 1.

At this point, we have discussed two ways of assessing pricing schemes, in which the latter, which we refer to as discrimination, is a descriptive measure. On the other hand, the prices that arise as a result of price differentiation must be assessed from a normative perspective.

5.3 Fairness, Redistribution and Ethical Considerations

We have discussed ways in which insurance companies may categorize their customer pools in order to be more competitive and reduce divergences between an insurance taker's price and expected losses, i.e., reducing discrimination based on irrelevant factors. In addition to assessing how efficient a pricing scheme is, we may consider other aspects of fairness. These questions of fairness will relate to how an insurance company prices individuals with different risk-relevant characteristics, and what responsibility we place on the individual for the outcome she faces.

We pose two normative views that we can use to consider the fairness of a market outcome. We consider that of efficiency-seeking, which coincides with actuarial pricing, and that of egalitarianism, motivated by a concern for the least well-off individual in a group. Our motivation for including these two views is that they represent two different considerations of fairness, in which most attitudes of fairness can be expressed as a mix of the two. We briefly discuss each idea, as well as how they will be specified in our analysis.

We first consider efficiency-seeking as a normative view, which coincides with the efficiency concepts described earlier. The first fundamental theorem of welfare economics states that competitive markets tend towards pareto optimality under a set of conditions (Mas-Colell, Whinston, & Green, 1995). One of these conditions is perfect information. We have shown that a competitive insurance market with perfect information yields actuarially fair prices to each type of insurance taker. Thus, we claim equivalency between acturial pricing and the optimal allocation of insurance according to the efficiency seeker.

The efficiency view can be seen in light of how much responsibility for an outcome we place on the individual. Referring back to the welfare theorem, efficiency is achieved when individuals and firms adapt to their economic environment. As such, an efficiency seeking social planner will pose that each individual is entirely responsible for their own situation. That one takes ownership of one's risk profile bears the implication that an actuarially fair price is deserved, and is deemed fair by society. If one is of high risk in nature, that is one's burden to bear, and there is no argument to impose subsidization.

Our second normative view is that of an egalitarian, motivated largely by a Rawlsian approach. In "A Theory of Justice", John Rawls (1971) presents a thought experiment in which members of a society are set to agree upon fundamental principles of justice before partaking in it. This situation is known as the original position. In taking up this point of view, members are to be free and equal in jointly agreeing upon and committing to principals of social and political justice. A distinguishing feature of the original position is the concept of "the veil of ignorance", which is set up to nullify the effects of specific contingencies that tempts one to exploit social and natural circumstances to one's own advantage, ensuring procedural justice in the societal construction. It is assumed that the parties are to an as large as possible degree unaware of their outcomes in life. This pertains to one's place in society, his class position or social status, as well as natural abilities and assets. Rawls aims for a setting in which, as far as possible, the only particular facts which the parties know is subject to the circumstances of justice and whatever it implies.

Rawls maintains that two principles spring out from the analysis. The first requires equality in the assignment of basic rights and duties, while the second holds that social and economic inequalities, are just only if they result in compensating benefits for everyone, and in particular for the least advantaged member of society. With these principles comes the notion of equality, either of opportunity to reach some desirable outcome, or of outcomes in themselves.

The egalitarian view may also be seen in light of individual responsibility in order to assess to what degrees outcomes should be regulated. We can consider to what extent an individual's outcomes are predetermined. In the language of insurance risk, one cannot be held responsible for having a health defect from birth, despite the obvious risk implications this can hold. There may be factors that an individual is able to affect, but we can also interpret the principles that arise from the original position so as to say that an individual is endowed with a set of abilities and motivations. In this rather extreme interpretation, we can say that an individual cannot be held responsible for anything, and equality of opportunities becomes equivalent to equality of outcomes. We pose this interpretation as a theoretical outset, and can qualitatively modify our views in our discussion.

We can illustrate the differences between the efficiency-seeking and egalitarian views graphically; consider planning a distribution of resources to two identical persons, A and B, illustrated in figure 8. Sending resources to person B comes at a cost double that of sending to person A, illustrated by the line with a gentle slope. We further illustrate the indifference curves of a efficiency seeker and an egalitarian. We see that the utility of the efficiency-seeking social planner is maximized by allocating all resources to person A, the most efficient outcome, while the egalitarian distributes resources so that both persons are equally well off. A person with a sense of fairness between the two extremes will have an indifference curve convex towards the origin and will choose a distribution between the two stated sets, somewhere on the bold part of the distribution line.

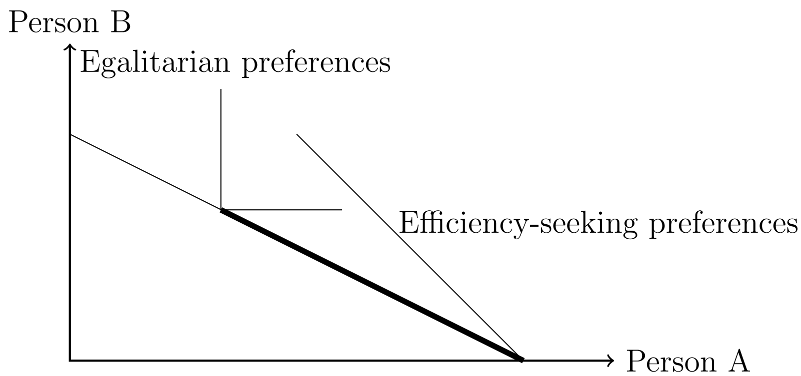


Figure 8: Efficiency-seeking vs egalitarian views of fairness

On a general level, the social planner can thus be said to be planning a distribution of resources by maximizing a social welfare function[16] subject to a resource constraint.

[16] This social welfare can typically be expressed as a constant elasticity of substitution (CES) welfare function with n individuals' endowments as arguments: $W(X_1, ..., X_n) = \left(\sum_{i=1}^{n} \alpha_i X_i^{-\rho}\right)^{-1/\rho}$ where $\sum_{i=1}^{n} \alpha_i = 1$ and $-1 \leq \rho \leq \infty$. The parameter ρ determines the degree to which the welfare planner weights efficiency versus equality. As ρ increases towards infinity, the elasticity of substitution approaches 0, implying Leontief preferences, i.e. egalitarianism. For more on the CES function, see for example: Nechyba (2011).

6 A Model of the Insurance Market

In the following, we attempt to model the implications big data may have on the insurance market. These implications will be connected to how well an insurance firm is able to categorize its potential customers as well as the composition of the market segment in question. We will model an insurance market with heterogeneous consumers and a competitive insurance market. We map out results for different compositions of insurance takers. Specifically, we simulate how the market composition changes after the introduction of stronger categorization that may follow from an increased utilization of big data in various settings.

Beyond just assessing better categorization through big data, our model considers the scenario in which members of higher social strata are enabled to signal their risk profiles, while low-SES individuals are unable to do so. In our model we will also be able to include a social gradient in risk, which reflects differences in risk between groups with different socioeconomic status. This brings in a social dimension in our model that is later used to consider the broader impacts of big data.

6.1 Model

We assume in our model that we have an population of insurance takers with a density from 0 to 1, with two social strata in it. These are divided into those that belong in a lower stratum, and those in a higher, denoted $j = L, H$ for those who are "low-SES" and those who are "high-SES", respectively. We use these two groupings to incorporate that the high-SES individuals may be privileged in the sense that they have opportunities that are exclusive to them. As described in the section for Socioeconomic Status (2.2.2), our division of SES does not necessarily translate into wealth or other traditional measures such as education and profession, but rather more intangible factors that may be advantageous to the high-SES individuals. These intangible factors are assumed to either be not be observed or not used by the insurance companies. This makes insurance companies unable to observe differences in SES within a population. In addition, as we show shortly, we can use the SES-grouping to add a social gradient in risk.

Insurance companies often categorize insurance takers into different segments based on different observable criteria. Within these segments we believe that there may still exist differences in socioeconomic status, which are explained by more intangible and unobservable factors. Our model will therefore enable us to analyze these insurance segments, and we can then think of our population of insurance takers as a specific insurance segment.

We denote the amount of low-SES individuals in the insurance population as θ, while the remaining high-SES individuals amount to $1 - \theta$. The distribution can be illustrated as in figure 9, and we note that θ is a parameter that may vary.

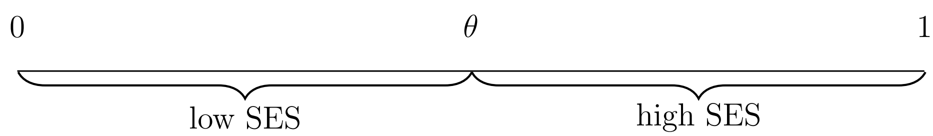


Figure 9: Population: Distribution of SES

Further, we assume there are two types of consumers of insurance in each socioeconomic stratum; those of high risk, and those of low risk, making a total of four groups. We go on to define the probability of losing an amount D as p^i, $i = l, h$, where $p^h > p^l$, which reflects individual risk. We denote the amount of low-risk individuals in the low-SES group as t_L, while the amount of low-risk individuals in the high-SES group is denoted t_H. The total amount of low-risk individuals is then $\tau = t_L + t_H \leq 1$, and the high risks will then amount to $1 - \theta + \theta - t_L - t_H = 1 - \tau$. In similar ways as in the the chapter for Theory (5), we can then define the average accident probability across the entire population as $\bar{p} = \tau p^l + (1 - \tau)p^h$. The average accident probability for the low-SES group is $\bar{p}^L = \frac{t_L}{\theta}p^l + \frac{(\theta - t_L)}{\theta}p^h$, and the average accident probability for the high-SES group is $\bar{p}^H = \frac{t_H}{1-\theta}p^l + \frac{(1-\theta-t_H)}{1-\theta}p^h$.

We define a social gradient in risk as the case in which the share of low-risk individuals is higher for the high-SES group than the low-SES group, i.e. $\frac{t_L}{\theta} < \frac{t_H}{1-\theta}$. The inequality comes about by adjusting the number of individuals for the respective SES-group sizes. A result that comes from this inequality relates to the average risk in each group, where $\bar{p}^L > \bar{p}^H$.

The distribution of the insurance population across socioeconomic groups as well as risk types, can be illustrated in figures 10 and 11, where we illustrate groups without and with a social gradient in risk, respectively.

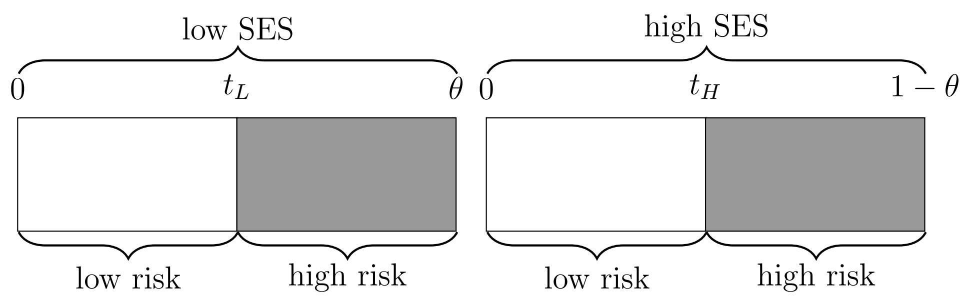


Figure 10: Population: Risk groups with no social gradient in risk

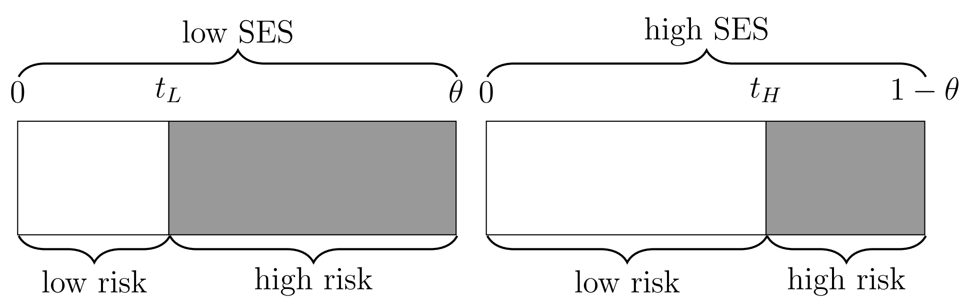


Figure 11: Population: Risk groups with a social gradient in risk

6.1.1 Supply of Insurance

Again, we assume a competitive market and that insurance companies maximizes the expected profit of a insurance contract (ω) given by:

$$\pi(p^i, \omega) = (1 - p^i) \underbrace{\alpha}_{\substack{\text{Profit w/o} \\ \text{accident}}} + p^i \underbrace{(\alpha - \beta)}_{\substack{\text{Profit w/} \\ \text{accident}}}$$

In insurance markets there are normally several different insurance contracts available for purchase. Some contracts are made available for everyone, and some contracts are designed specifically and offered exclusively to certain groups or types. We will consider several scenarios throughout this chapter, where we consider that insurance companies may have varying opportunities to categorize insurance takers into specific groups. By doing so, the insurance companies can effectively choose to differentiate specific groups of the population by offering different contracts to different groups. We define the total supply of insurance in its most general form as a vector of contracts that each consist of indemnities β^{ij} and their respective premia α^{ij} for all types of consumers we consider:

$$\boldsymbol{\omega} = (\boldsymbol{\alpha}, \boldsymbol{\beta}) = \begin{pmatrix} \alpha^{lL} & \beta^{lL} \\ \alpha^{hL} & \beta^{hL} \\ \alpha^{lH} & \beta^{lH} \\ \alpha^{hH} & \beta^{hH} \end{pmatrix}$$

6.1.2 Demand for Insurance

We set up the insurance demand as described in the chapter for Theory (5). The consumers each have a utility function $U = U(W, D)$ that depends on their final wealth in the case in which a loss occurs and the one in which wealth is unaffected. Under the expected utility theorem, preferences for wealth in the two states will be described by a function of the form:

$$\hat{V}^{ij}(p^i, W, D) = (1-p^i)U(W) + p^iU(W-D)$$

If there exists an insurance contract with a premium α^{ij} and an indemnity β^{ij}, the von Neumann - Morgenstern expected utility of an insured individual with risk type $i = l, h$ and SES $j = L, H$ will be:

$$\hat{V}^{ij}(p^i, W, D, \alpha^{ij}, \beta^{ij}) = (1-p^i)U(W-\alpha^{ij}) + p^iU(W-D-\alpha^{ij}+\beta^{ij})$$

For simplicity in notation we can consider the case in which an accident does not occur as $W_1^{ij} = W - \alpha^{ij}$ and $W_2^{ij} = W - D - \alpha^{ij} + \beta^{ij}$. Totally differentiating and keeping expected utility constant as previously shown yields:

$$\begin{aligned} 0 &= (1-p^i)U'(W_1^{ij})dW_1^{ij} + p^iU'(W_2^{ij})dW_2^{ij} \\ \rightarrow -\frac{dW_2^{ij}}{dW_1^{ij}} &= \frac{1-p^i}{p^i}\frac{U'(W_1^{ij})}{U'(W_2^{ij})} = MRS^{ij} \end{aligned}$$

The Marginal Rate of Substitution tells us how much an individual requires to be compensated in the unfortunate state for giving up a unit of wealth in the lucky state[17]. If the probability of a loss increases, the willingness to reduce wealth in the good state to purchase insurance increases.

To ensure the single-crossing condition of indifference curves, we assume that SES has no effect on the shape of the curves. We will discuss this assumption in the next chapter. For now, we only note that this assumption means that all individuals have identical initial endowments of wealth, regardless of SES type. As before stated, the odds-ratio will then be the only factor affecting the marginal rate of substitution for each risk type. As $p^l < p^h$

[17] $\frac{1}{MRS}$ tells us how much of your wealth in the fortunate state you are willing to give up, to increase your wealth by one unit in the unlucky state.

we can assume the following:

$$MRS^{lj} > MRS^{hj}, j = L, H$$

Implying that the rate of substitution for a low-risk individual (independent of SES) is higher than for their high risk counterparts, meaning they are less willing to exchange wealth in the lucky state for insurance in the loss state.

6.2 Application of Model

We have in the preceding section set up parameters that define our insurance group. We now use the theory presented earlier to assess potential market outcomes in different scenarios. These scenarios are analyzed in two market-settings; one in which full insurance coverage is mandatory, and one in which it is not.

The market outcomes will have implications for the various types of individuals that we have defined. For each scenario, we specify outcomes absent of big data (i.e. the initial state), followed by outcomes brought about by the introduction of big data. Big data is introduced by allowing individuals to perfectly signal their true risk type. Note that the incentive for signalling is always present for low-risk individuals, as they are then offered an actuarially fair contract. We present two types of scenarios of big data introduction; one in which signalling is available to everyone, and one in which only high-SES individuals are able to signal. Throughout the analysis, we consider the effect of a social gradient in risk.

Our main unit of analysis is how outcomes change, from the initial state to the "big data" state. The outcome changes are typically brought about by new contracts offered to different groups of our population. Thus, we will consider how prices and amount of coverage offered to certain groups, changes in the two states. From this, we can determine how individual welfare for different groups changes as well as the overall welfare in the population.

6.3 Mandatory Insurance

We first apply our model framework in a setting in which full coverage is mandatory, meaning we exogenously have $\beta^{ij} = \beta^* = D$ for all i, j. This corresponds to a linear pricing scheme with an intervention, as discussed under Linear Insurance Contracts (5.1.2). Our outcome variable of interest will thus be the premium α^{ij} that is offered to the various groups, and how well it reflects the expected cost of its group. The underlying assumption is still that insurance companies are competitive, and the persisting contracts will be the ones that most closely reflect the insurance takers' individual risks.

In the initial state, we assume that the insurance companies are unable to identify an individual's risk. However, the insurance companies knows the total share of low-risk and high-risk individuals in the population, meaning $\tau = t_L + t_H$ is known. In order to break even, the insurance companies will initially charge an average premium, $\bar{\alpha} = \bar{p}D$[18], to everyone. We note that we are then in a situation where the low risks are subsidizing the high risks in the population. In addition, if there exists a social gradient in risk, the low-SES group will to some degree be subsidized by the high-SES group. The contract set is then given by:

$$\boldsymbol{\omega} = (\boldsymbol{\alpha}, \boldsymbol{\beta}) = \begin{pmatrix} \alpha^{lL} & \beta^{lL} \\ \alpha^{hL} & \beta^{hL} \\ \alpha^{lH} & \beta^{lH} \\ \alpha^{hH} & \beta^{hH} \end{pmatrix} = \begin{pmatrix} \bar{\alpha} & \beta^* \\ \bar{\alpha} & \beta^* \\ \bar{\alpha} & \beta^* \\ \bar{\alpha} & \beta^* \end{pmatrix} \Rightarrow \boldsymbol{\alpha} = \begin{pmatrix} \alpha^{lL} \\ \alpha^{hL} \\ \alpha^{lH} \\ \alpha^{hH} \end{pmatrix} = \begin{pmatrix} \bar{\alpha} \\ \bar{\alpha} \\ \bar{\alpha} \\ \bar{\alpha} \end{pmatrix}$$

where again β^* is the exogenously given full level of insurance that must be acquired. For simplicity we omit the $\boldsymbol{\beta}$-vector in the remainder of this section, as it will remain constant as long as the required coverage is given equally to all individuals. What is thus of interest, is the vector $\boldsymbol{\alpha}$ which describes the various prices offered to different individuals in our insurance groups.

[18] $\bar{\alpha} = \tau\alpha^{l*} + (1-\tau)\alpha^{h*} = \tau p^l D + (1-\tau)p^h D = (\tau p^l + (1-\tau)p^h)D = \bar{p}D$, where $\alpha^{i*} = p^i D$ is the actuarially fair premium for risk type i.

6.3.1 Introducing Perfect Signalling

We have to this point illustrated how we may expect an insurance market with mandatory coverage to behave. We now introduce signalling to our model. As this is a relatively new concept, and its consequences are not yet known, we consider various ways in which the insurance market may be affected. As such, we simplify by modelling big data as insurance companies' observation of insurance takers' signals. A simple example of a signal may be observation of certain health statistics, such as daily steps, counted by a fitness tracker. In this setting, low risk may be correlated with a certain amount of daily steps. Further, we assume that an individual may only signal her true type, and that low-risk individuals will always have an incentive to signal their type.

We first consider the case in which big data allows for perfect categorizing of all individuals through perfect signalling available to all insurance takers. Big data will bring about the contract $(\boldsymbol{\alpha^*}, \boldsymbol{\beta^*})$. In other words, each risk group will be, regardless of SES-type, charged a premium which perfectly reflects their respective risk ($\alpha^{i*} = p^i D$). This can be thought of as an enabling of individuals to signal their true type without a cost, and no possibility of signalling the wrong type[19]. In our fitness-tracker example, this means high-risks will not walk the amount of steps that is correlated with the low-risk category. All low-risk individuals will signal their type, and by deduction, the insurance companies will know that the remaining individuals are of high risk.

$$\boldsymbol{\alpha} = \begin{pmatrix} \alpha^{lL} \\ \alpha^{hL} \\ \alpha^{lH} \\ \alpha^{hH} \end{pmatrix} = \begin{pmatrix} \alpha^{l*} \\ \alpha^{h*} \\ \alpha^{l*} \\ \alpha^{h*} \end{pmatrix} = \boldsymbol{\alpha^*}$$

The actuarially fair premia which is brought about will remove the initial cross-subsidization, making every low risks better off and every high risks worse off than before. If there ex-

[19] We assume that it is without cost to signal true type, and infinitely costly to signal the low risk if one is truly of high risk.

ists a social gradient in risk we note that this will make the low-SES group overall worse off, since they will have a higher share of high risks than the high-SES group. Since full coverage is mandatory there will be no changes in overall welfare in the population.

6.3.2 Introducing Exclusive Signalling

As before, the ability to signal true type exists, but we now assume that it is exclusive to high-SES individuals. This advantage can relate to for example privileges, economic status, relevant knowledge, or networks. In our example, we can view this as a scenario in which only members of the upper strata have access to and utilize fitness trackers, such as FitBit, Apple Watch and the likes. Individuals of high SES and low risk will have an incentive to signal their type, and the insurance companies (given some competitiveness in the insurance market) will offer these the premium $\alpha^{l*} = p^l D$. The remaining groups in the population will receive a premium based on their average risk. The average price to break even, given the remaining pool, is then: $\alpha' = \frac{t_L}{\theta}\alpha^{l*} + \frac{(\theta - t_L)}{\theta}\alpha^{h*} + \frac{(1-\theta-t_H)}{1-\theta}\alpha^{h*}$. The menu of contracts is thus:

$$\boldsymbol{\alpha} = \begin{pmatrix} \alpha^{lL} \\ \alpha^{hL} \\ \alpha^{lH} \\ \alpha^{hH} \end{pmatrix} = \begin{pmatrix} \alpha' \\ \alpha' \\ \alpha^{l*} \\ \alpha' \end{pmatrix}$$

Given that signalling is exclusive to high-SES individuals, we see that the high-SES low-risks are taken out of the general segment, and receive the actuarially fair premium α^{l*}. The remaining individuals receive an average premium higher than before, making them all worse off, since they lose some of the cross-subsidiziation. We note that the high-risk individuals are still somewhat subsidized by the low-risks in the lower stratum, yielding them some positive discrimination.

An interesting result we find is that low-SES individuals are overall harmed in this scenario, independent of the existence of a social gradient in risk ($\alpha' > \bar{\alpha}$ regardless of whether $\frac{t_L}{\theta} < \frac{t_H}{1-\theta}$ or $\frac{t_L}{\theta} = \frac{t_H}{1-\theta}$). Due to the low-SES, low-risks' inability to escape the pooling contract, they are left to subsidize all the high risks without the "help" of the high-SES low risks. Thus, the smaller the relative size of $\frac{t_L}{\theta}$, the larger the negative discrimination this group is left to face. We can summarize our degrees of discrimination for all four groups relative to the situation without big data:

Table 1: Discrimination

Risk group	Post big data vs Pre big data
Low-SES, low-risk:	$\frac{\alpha'}{\alpha^{l*}} > \frac{\bar{\alpha}}{\alpha^{l*}}$
Low-SES, high-risk:	$\frac{\alpha'}{\alpha^{h*}} > \frac{\bar{\alpha}}{\alpha^{h*}}$
High-SES, low-risk:	$\frac{\alpha^{l*}}{\alpha^{l*}} < \frac{\bar{\alpha}}{\alpha^{l*}}$
High-SES, high-risk:	$\frac{\alpha'}{\alpha^{h*}} > \frac{\bar{\alpha}}{\alpha^{h*}}$

Showing that everyone is made worse off to varying degrees, except the high-SES, low-risk group. Further, the total amount of discrimination post big data can be written as the following relationship:

$$\underbrace{t_L \frac{\alpha'}{\alpha^{l*}}}_{\text{negative discrimination}} = \underbrace{(1-t_L)\frac{\alpha'}{\alpha^{h*}} + (1-\theta-t_H)\frac{\alpha'}{\alpha^{h*}}}_{\text{positive discrimination}}$$

Showing that a relatively small amount of low-SES individuals need to carry the entire burden of subsidizing the high-risk individuals. Since also the high-risk individuals are charged higher prices, this means that some of the initial negative discrimination is absorbed by themselves.

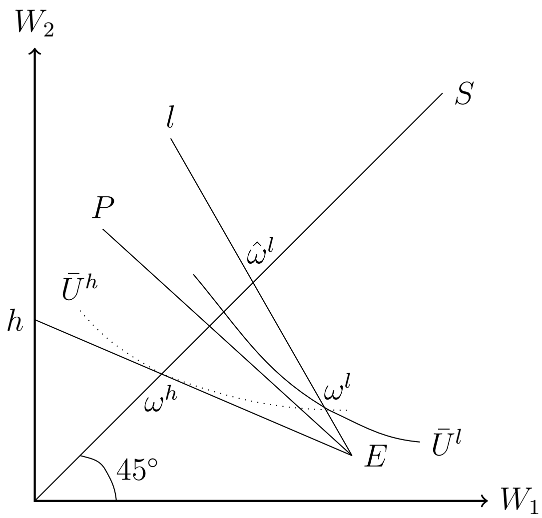
6.4 Non-linear Contracts

We now consider an unregulated market, where the indemnity is decided endogenously. This is the case where the insurance company can use both premium(α) and indemnity(β) as instruments in designing optimal contracts, i.e. non-linear contracts. We consider both separating self-selection contracts and pooling contracts offered, depending on the composition of risk types in the population. Equilibria are derived using an adapted framework from Rothschild and Stiglitz (1976) and Wilson (1977).

As before we have argued that if SES has no effect on the wealth endowment of an individual, we can pose that $MRS^{iH} = MRS^{iL}$, implying that initially, only the probability of a loss affects the MRS of an individual. This in turn implies that the rate of substitution for a low-risk individual (independent of SES) is higher than for their high risk counterparts, meaning they are less willing to exchange wealth in the lucky state for insurance in the loss state.

As before, we assume that the insurance companies are unable to observe SES. In other words, the insurance companies have no ability to treat the insurance takers differently depending on their SES-type. In addition, the insurance companies has no possibility of identifying an individual's risk. However, the insurance companies know the total share of low-risk and high-risk individuals in the population. We pose that both separating and pooling equilibria are plausible in the outset, depending on the total amount of high-risks across both socioeconomic groups (τ).

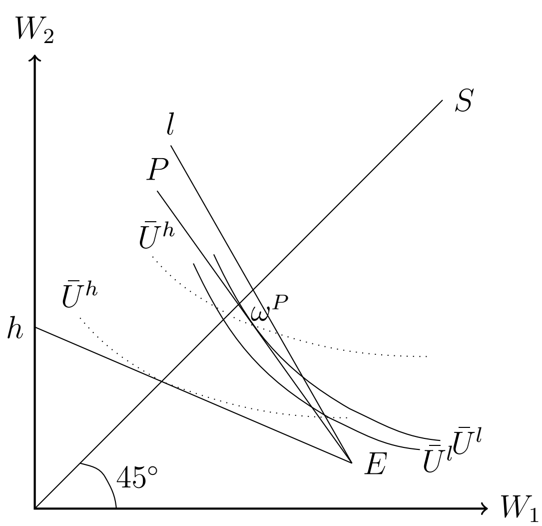
First, we can consider the case in which the total share of high risk types in the population is sufficiently large for there to exist a RS separating equilibrium. This situation is depicted in figure 12 with the set of separating contracts (ω^h, ω^l) which is offered to everyone. Intuitively, this means that insurance companies are offering two contracts to everyone in the population. The contracts are designed to incentivize self-selection, so every high-risk individual will choose contract ω^h and every low risk will choose contract ω^l. Based on reasoning from earlier, it is also worth noting that if the insurance companies were able to distinguish the different risk types in the population, and offer different contracts directly to each respective risk type, the optimal contracts offered would be $(\omega^h, \hat{\omega}^l)$.



$$\boldsymbol{\omega} = \begin{pmatrix} \alpha^{lL} = \alpha^{l*} = p^l \beta^{lL} & , \beta^{lL} < D \\ \alpha^{hL} = \alpha^{h*} = p^h \beta^{hL} & , \beta^{hL} = D \\ \alpha^{lH} = \alpha^{l*} = p^l \beta^{lH} & , \beta^{lH} < D \\ \alpha^{hH} = \alpha^{h*} = p^h \beta^{hH} & , \beta^{hH} = D \end{pmatrix}$$

Figure 12: Initial Equilibrium: Separating

Second, we can consider the case in which the total share of high risk types in the population is *not* sufficiently large for there to exist a RS separating equilibrium. In this case there will not exist an equilibrium in the Rothschild & Stiglitz framework. However, if we use the Wilson E2 Equilibrium concept, we may derive a pooling equilibrium. The pooling equilibrium contract ω^P, depicted in figure 13, will be offered to everyone.



$$\boldsymbol{\omega} = \begin{pmatrix} \alpha^{lL} = \bar{\alpha} = \bar{p} \beta^{lL} & , \beta^{lL} < D \\ \alpha^{hL} = \bar{\alpha} = \bar{p} \beta^{hL} & , \beta^{hL} < D \\ \alpha^{lH} = \bar{\alpha} = \bar{p} \beta^{lH} & , \beta^{lH} < D \\ \alpha^{hH} = \bar{\alpha} = \bar{p} \beta^{hH} & , \beta^{hH} < D \end{pmatrix}$$

Figure 13: Initial Equilibrium: Pooling

6.4.1 Introducing Perfect Signalling

As in the case presented earlier with mandatory insurance in which perfect signalling brings about perfect categorization, the optimal contract set $(\omega^h, \hat{\omega}^l)$ is achieved. The insurance companies offer $\hat{\omega}^l$ to the low risks who signal their risk type. And by deduction, the remaining high risks are offered ω^h. This means that low risks and high risks achieve full insurance at their respective fair prices.

$$\boldsymbol{\omega} = (\boldsymbol{\alpha}, \boldsymbol{\beta}) = \begin{pmatrix} \alpha^{lL} = \alpha^{l*} = p^l \beta^{lL} & , \beta^{lL} = D \\ \alpha^{hL} = \alpha^{h*} = p^h \beta^{hL} & , \beta^{hL} = D \\ \alpha^{lH} = \alpha^{l*} = p^l \beta^{lH} & , \beta^{lH} = D \\ \alpha^{hH} = \alpha^{h*} = p^h \beta^{hH} & , \beta^{hH} = D \end{pmatrix}$$

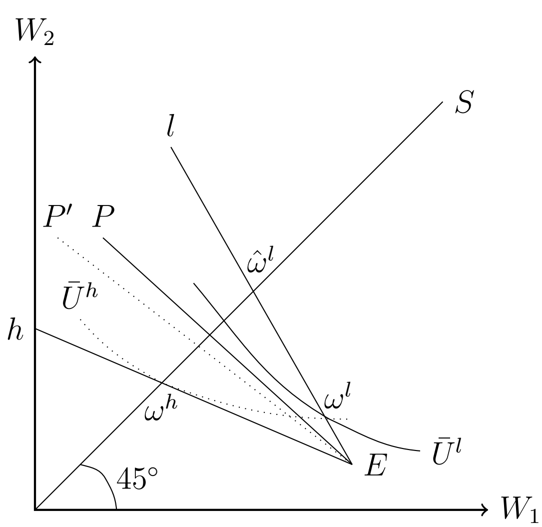
If there is a large share of high risk types in the population, and the insurance companies initially offered separating contracts to everyone, perfect signalling of risk types yields a Pareto improvement in the market. The low risks in the whole population are better off (going from contract ω^l to $\hat{\omega}^l$ and achieving a higher utility level), while the high risks receive the same contract as before. If there exists a social gradient it is worth noting that this efficiency gain is mainly absorbed by high-SES types since their share of low risks are higher.

If there is a small share of high risk types in the population, and the insurance companies initially offered a pooling contract, perfect signalling of risk types may yield a Kaldor-Hicks improvement. Even though everyone now pays their actually fair price, high-risk types will now have to pay a lot more than they initially did. It will be a Kaldor-Hicks improvement if the small gains of the many low risks outweighs the large losses of the few high risks. If there is a social gradient, this means that it is the larger share of high risks in the low SES group which is the big loser in this scenario.

6.4.2 Introducing Exclusive Signalling

As we have seen, the high-SES low-risk group will have an incentive to signal their type, and thus receive full insurance at their acturially fair premium. Neither the high risk types in the high-SES group nor in the low-SES group will be acknowledged as high risks through deduction by the insurance company. We can then imagine that the low risks in the high-SES are removed from the total pool of insurance takers and offered full insurance at their actuarially fair premium. The remaining pool of insurance takers will then include a lower share of low risks, which will pivot the pooling zero-profit line $\overline{EP}$ downwards.

First we can consider the case in which there is a large share of high risk types in the population, and the insurance companies initially offered separating contracts to everyone. A pivot of the pooling zero-profit line $\overline{EP}$ downwards to $\overline{EP'}$, as depicted in figure 14, will not change the separating equilibrium. Exclusive signalling will therefore not change the contracts offered to the remaining pool, leaving them unaffected by the introduction of big data.

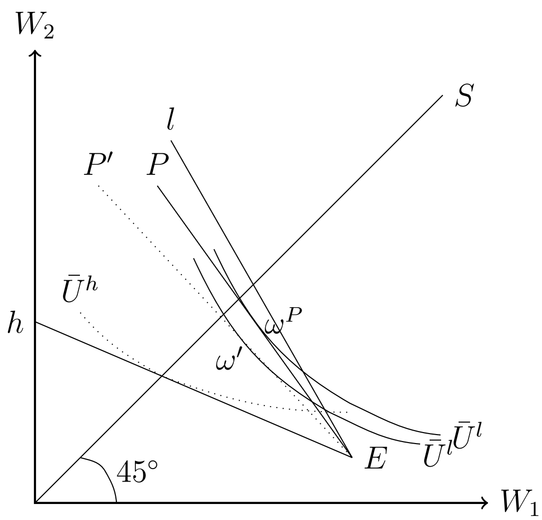


$$\boldsymbol{\omega} = \begin{pmatrix} \alpha^{lL} = \alpha^{l*} = p^l \beta^{lL} & , \beta^{lL} < D \\ \alpha^{hL} = \alpha^{h*} = p^h \beta^{hL} & , \beta^{hL} = D \\ \alpha^{lH} = \alpha^{l*} = p^l \beta^{lH} & , \beta^{lH} = D \\ \alpha^{hH} = \alpha^{h*} = p^h \beta^{hH} & , \beta^{hH} = D \end{pmatrix}$$

Figure 14: Large share of high risks and Exclusive Signalling: Separating Equilibrium

The story is quite different if we consider the case in which there is a small share of high risk types in the population, and the insurance companies initially offered a pooling contract to everyone. In this case, the pivot of the pooling zero-profit line $\overline{EP}$ downwards to $\overline{EP'}$ will have two potential outcomes.

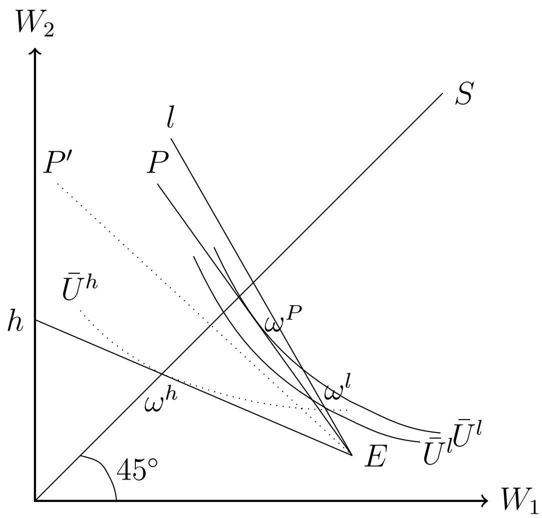
If we assume that the share of high risk in the remaining pool is still sufficiently low, after the low risks from the high-SES group is removed, we can still derive a pooling equilibrium. This pooling equilibrium is depicted as ω' in figure 15, and lies south-west of the initial pooling equilibrium (ω^P). In other words, the remaining pool of insurance takers will be offered a new contract with a higher average premium and less coverage than before.



$$\boldsymbol{\omega} = \begin{pmatrix} \alpha^{lL} = \alpha' = \bar{p}'\beta^{lL} & , \beta^{lL} < D \\ \alpha^{hL} = \alpha' = \bar{p}'\beta^{hL} & , \beta^{hL} < D \\ \alpha^{lH} = \alpha^{l*} = p^l\beta^{lH} & , \beta^{lH} = D \\ \alpha^{hH} = \alpha' = \bar{p}'\beta^{hH} & , \beta^{hH} < D \end{pmatrix}$$

Figure 15: Small share of high risks and Exclusive Signalling: Pooling Equilibrium

Another scenario is that the share of high risk in the remaining pool is not sufficiently low. We are then in a situation where the pooling zero-profit line pivot downwards, below the indifference curve of the low risks which goes through the contract ω^l, depicted in figure 16. The insurance companies will then change their strategy and offer separating contracts (ω^h, ω^l) to everyone in the remaining pool.



$$\boldsymbol{\omega} = \begin{pmatrix} \alpha^{lL} = \alpha^{l*} = p^l \beta^{lL} & , \beta^{lL} < D \\ \alpha^{hL} = \alpha^{h*} = p^h \beta^{hL} & , \beta^{hL} = D \\ \alpha^{lH} = \alpha^{l*} = p^l \beta^{lH} & , \beta^{lH} = D \\ \alpha^{hH} = \alpha^{h*} = p^h \beta^{hH} & , \beta^{hH} = D \end{pmatrix}$$

Figure 16: Small share of high risks and Exclusive Signalling: Separating Equilibrium

Thus, in the situation where there is a small share of high risks in the population, exclusive signaling will make everyone but the low risks in the high-SES group worse off. We also note that if there is a relatively large amount of low risks in the high-SES group, exclusive signalling will more likely result in a separating contract set offered to the remaining pool of insurance takers. In comparison with the initial pooling contract, the remaining pool will be far worse off then they were before. The remaining high risks will purchase full insurance, but at a fair price which is a lot higher than before. The low risks will purchase insurance at a fair price, which is lower than before, but will also be worse off since they will have to decrease their coverage substantially.

6.5 Perfect Signalling of SES

So far we have considered the case in which big data may allow insurance takers to signal their risk type. Another possibility is that big data will allow for signalling of an individuals' socioeconomic status. We can think of this as signalling of typically intangible factors that could explain differences in socioeconomic status. These factors are what we until now have assumed to be unobservable for the insurance companies. The analysis of this scenario is included in the appendix.

The findings are similar to what we already have found. If there exists a social gradient in risk, perfect signalling of SES-type will typically make the low-SES group worse off or at best unaffected. At the same time the high-SES group are typically better off or at worst unaffected. This comes from the fact that the low-SES group is initially to some degree subsidized by the high-SES group. Perfect signalling of SES-type will allow the insurance companies to treat these groups separately, removing this cross-subsidization.

7 Discussion

We have presented a framework designed to analyze the effects of better categorization in an insurance market. This categorization is brought about by either exclusive or inclusive (i.e. perfect) signalling, and we believe this will be relevant as utilization of big data grows in the insurance markets. Dependent on the characteristics of an insurance product segment, we can make predictions regarding how specific groups will be affected by the introduction of big-data models. The following parameters need to be specified for an insurance segment.

First, we need to consider to what degree the market is regulated, meaning where on a spectrum between the scenarios of mandatory insurance and a free market we find our segment to be. In considering the consumer composition, we need to consider whether a product segment has a problem of adverse selection, meaning whether or not there are different risk types in which the insurance companies do not have the ability of uncovering at the outset. Further, the relative size and existence of different socioeconomic groups within a product segment must be considered. This means that we assess whether there exists subgroups within the segment which may have some potential advantage in signalling to a big-data model, making them relatively "high SES". Related to this, we need to make a statement as to whether big-data models will perform a categorization based on perfect signalling or exclusive signalling. Lastly, the consideration as to whether a social gradient in risk exists will have implications for what outcome we believe is plausible to arise as big data is taken into use.

In the tables below, we summarize the outcomes that arise for our different groups, given the variables we have described. For each group we specify whether they benefit or are harmed by the improvement in categorization, in both the cases for perfect and exclusive categorization. This change is measured as a change in utility. Thus, as utility is an ordinal measure, we can only specify directions and not magnitudes.

In the case of mandatory insurance, the possible outcomes are summarized in table 2. Since amount of coverage is exogenously given and constant, changes in utility reflect only changes in premia charged to different groups. We note that there are two ways the low-SES can be harmed in this setting. First, if there exists a social gradient in risk the low-SES group will initially to some degree be subsidized by the high-SES group. They will initially be charged the same premium, while the probability of a randomly drawn insurance taker incurring a loss will be larger in the low-SES group ($\bar{p}^L > \bar{p} > \bar{p}^H$). Better categorization will reduce this subsidization, making the low-SES worse off as a whole. Second, low-SES groups can be harmed by better categorization if there exists exclusive opportunities of signalling true risk-type. If only the low risks in the high-SES group are able to signal their true type, they will be recognized and treated separately by the insurance companies. Thus, only the remaining low risks in the low-SES group are left to subsidize all the high risks. The premium charged to the remaining pool of insurance takers will then increase, making them all worse off. This result holds independent of a social gradient.

Table 2: Mandatory Insurance

Scenario\Group	lL	hL	Low-SES	lH	hH	High-SES
i) Perfect Signalling *	Better (Better)	Worse (Worse)	**Worse (Unaffected)**	Better (Better)	Worse (Worse)	Better (Unaffected)
ii) Exclusive Signalling: *	Worse (Worse)	Worse (Worse)	**Worse (Worse)**	Better (Better)	Worse (Worse)	Better (Better)

*We assume that a social gradient in risk exists. The case in which a social gradient does not exist is given by outcomes in parentheses.

Outcomes in the case of no regulation and non-linear contracts are summarized in tables 3 and 4. As described in the previous chapter, the initial contracts offered to the insurance takers will depend on the composition of the population.

First we summarize the outcomes in the case of a sufficiently large share of high-risks in the population for there to initially exist a separating contract equilibrium. In this case the insurance companies will initially offer two, rather than one single contract. These contracts offered are designed for self-selection. An interesting aspect of this scenario is that all high-risks in the population will then initially choose the contract with full insurance and a premium which fully reflects their risk. This is also the contract that insurance companies would offer them if they were able to identify them. Thus, if insurance companies introduce new techniques to uncover high risks in the population they will not have any incentives to offer them a different contract, leaving the high risks unaffected in every potential scenario. On the other hand, for separating contracts to be efficient, the other contract offered in the market must not be preferred by the high risks, while being preferred by the low risks. The result is a contract with a low premium and a much lower coverage that is only preferred by the low risks. Thus, if better categorization of insurance takers is introduced, this will benefit the low risks, while not affecting the high risks. Given perfect signalling of risk type, we can then conclude that there will be a Pareto improvement in both socioeconomic groups. In the case where only high-SES are able to signal their type, only the low risks in the high-SES group will receive a better contract.

Table 3: Non-linear contracts: large share of high-risks: separating equilibrium

Scenario\Group	lL	hL	Low-SES	lH	hH	High-SES
iii) Perfect Signalling *	Better (Better)	Unaffected (Unaffected)	**Better (Better)**	Better (Better)	Unaffected (Unaffected)	Better (Better)
iv) Exclusive Signalling: *	Unaffected (Unaffected)	Unaffected (Unaffected)	**Unaffected (Unaffected)**	Better (Better)	Unaffected (Unaffected)	Better (Better)

*We assume that a social gradient in risk exists. The case in which a social gradient does not exist is given by outcomes in parentheses.

If there is a sufficiently small share of high risks in the population the story is quite different. We are now in a situation where there does not exist an initial separating equilibrium, but we can derive a pooling equilibrium. This case is more similar to the case of mandatory insurance, in which the insurance takers are offered a single contract with an average premium. The only difference is that insurance companies now specify the amount of coverage that they are allowed to purchase. Again, since there is a only a single contract offered, it means that the low risks are subsidizing the high risks in the population. If there exists a social gradient this means that the high-SES group are to some degree subsidizing the low-SES group. In contrast to separating contracts, introduction of better categorization will now benefit the low risks, while harming the high risks. Pareto improvements are therefore not a possibility, but we may talk about possible Kaldor-Hicks improvements.

As mentioned in the previous chapter, when the share of high risks is relatively small, the overall welfare changes as a result of better categorization are often unclear. Perfect categorization will dramatically increase premia charged to the small share of high risks in the population, while giving a small reduction in premia charged to the large share of low risks. To precisely derive the overall outcomes for certain groups we therefore need to specify all parameters in the model before and after new categorization. We have not done this, but we do argue later in this chapter that in some cases it is more likely that the low-SES group are overall worse off. What we can say at this point, is that if there exist a social gradient in risk, the big loser in this setting is the relatively large share of high risks in the low-SES group.

Further, if there are any exclusive opportunities for only high-SES to signal their true type, we can with certainty state that everyone in the low-SES segment are made worse off. If only the low risks in the high-SES group are uncovered, the remaining pool of insurance takers will either be offered: 1) a new pooling contract with a higher premium and lower coverage or 2) a set of separating contracts. In both cases, the new contracts offered will yield a utility level lower than before.

Table 4: Non-linear contracts: small share of high-risks: pooling equilibrium

Scenario\Group	lL	hL	Low-SES	lH	hH	High-SES
v) Perfect Signalling *	Better (Better)	Worse (Worse)	**Unclear (Unclear)**	Better (Better)	Worse (Worse)	Unclear (Unclear)
vi) Exclusive Signalling:** *	Worse (Worse)	Worse (Worse)	**Worse (Worse)**	Better (Better)	Worse (Worse)	Unclear (Unclear)

*We assume that a social gradient in risk exists. The case in which a social gradient does not exist is given by outcomes in parentheses.
** Two scenarios: Exclusive signalling makes insurance companies offer either a new pooling contract or a separating contract set to the remaining pool of insurance takers. In both cases, the remaining pool of insurance takers will be worse off.

Hoy (1982) shows in his paper "Categorizing Risks in the Insurance Industry" that the welfare implications of imperfectly categorizing risks depends on the initial equilibrium. He analyzes the insurance market using both the RS equilibrium and the Wilson E2 equilibrium. He finds that only if the initial equilibrium is of the no-subsidization type, there will be a Pareto improvement in welfare (Hoy, 1982). As we know from before, the RS separating equilibrium is a no-subsidization equilibrium. Our results are thus consistent with this.

We see that the general tendency for the low-SES group is one of adversity, as can be seen from the fourth column in the preceding tables, denoted in bold. Despite differences in risk within SES-groups, we find that at best, their overall welfare remains unaffected, save for scenario iii). We believe that different scenarios may be suited for describing various product segments within different insurance markets, such as health- and life-insurance and property- and casualty-insurance. In property- and casualty-insurance there will for example often exist a minimum required level of car insurance. In Norway it is mandatory for car owners to purchase liability insurance, which covers injury to persons and damages to other vehicles, buildings and objects. In the market for car insurance, as well as others, we have less reason to assume that there exists a social gradient in risk. However, even if there does not exist a social gradient in risk, we note that the low-SES individuals of these markets may be harmed by inabilities to signal their risk type.

7.1 Trends in the Health- and Life-Insurance Market

In this section we perform an application of our model on the market for private health- and life-insurance in Norway. Our motivation for this bases itself on several factors. First, as we discussed in The Social Gradient in Risk (2.2.3), we believe a social gradient will be strongly present in this market, yielding interesting and clear results. Second, in the property- and casualty-type of insurance-markets we have seen a development of new insurance products which classifies risk based on behaviour. In the health- and life-insurance market the same trend exists, but to a smaller extent. As we have mentioned earlier, there are no such products available for purchase in the Norwegian market. Personal information about health is typically more sensitive than data on e.g., driving behaviour, and we know from the privacy survey conducted by the Norwegian Data Protection Authority (2016) that Norwegians are generally more skeptical to sharing data on personal health indicators and physical activity. The new privacy regulation (GDPR) will strengthen individual control of personal information shared with insurance companies and increase the privacy requirements for insurance companies handling these data. Better regulation is argued to ultimately reduce the barriers of sharing sensitive information. In addition, if the new insurance products in the property- and casualty-market turns out to be a success for both the insurance companies and the insurance takers, we can argue that the concept will establish itself in the health- and life-insurance market as well.

Lastly, there is much discussion as to whether health insurance should be offered privately or publicly, and an analysis of the former may bring more insight to the debate. The "welfare state"[20] has strong roots in Norway and is characterized by universal welfare rights, which means that everyone has equal rights to welfare benefits. Thus, regardless of different social aspects, Norwegians have equal access to public health services, education etc. (Christensen & Berg, 2017). We have shown that using big data in a private market will lead to more individualized insurance policies, reducing the pooling of risk across

[20]A state, which to a significant extent, guarantees members of the society help in case of illness, social emergency, or loss of income, for example due to unemployment or old age, and which ensures the individuals' right to education (Christensen & Berg, 2017).

larger groups. In contrast, the Scandinavian welfare-model builds on equalizing as a principle (Karlstad, 2010). In the cases where the welfare state provide insurance, no one is treated differently based on their individual risk.

Our goal is to use the insight from our framework, combined with the structure of the health- and life-insurance market in Norway to assess how individuals with a low socioeconomic status within this market may be affected in the future. We note that there are many uncertainties regarding the future, and that the real world is far more complex than a model. Despite this, we do our best to give an indication through a structured and analytical approach.

We go on to define private health- and life-insurance as different types of personal insurance[21] and individual capital insurance[22]. To assess the trend which may occur in this market from the development of big data, we decide to focus on the insurance products with the largest overall premia. We collect key figures on premia paid by Norwegian insurance takers in 2016 from Finance Norway (Finance Norway, 2016). The key figures are presented in table 5, and we find that life- and disability-insurance are the largest products. Assessing how we believe the future of these products will be, will therefore give a good indication for the overall trend in the market.

Table 5: Private Health- and Life-insurance: Premiums

Private Health- and Life-insurance	Premiums 2016 (MNOK)
i) Personal Insurance:*	
Children Insurance	1,414.7
Accident Insurance	780.2
Treatment Insurance	173.3
Critical illness Insurance	606.6
Other products	234.9
ii) Individual Capital Insurance:**	
Life- and Disability-insurance	14,112.9

*Premiums: Premiums for all insurance policies in force at the reporting time.
**Gross Written Premiums: All premiums that are due for payment during the year.

[21]Personal insurance is a collective term on different insurance products within life and health.
[22]A capital insurance means that the insurance provides a one-time payment. The insurance can consist of a risk coverage for death and/or disability, as well as being in combination with savings.

7.1.1 Social Gradient in Risk

First of all, we can establish that there is asymmetric information in the market for life- and disability-insurance. Insurance takers will typically have private information about their own risk that insurance companies do not know. Further, we need to consider whether there exists differences in socioeconomic status within different segments of insurance takers in this market. Finally, we need to consider the existence of a social gradient in risk. We know, based on earlier reasoning, that on a general level there exists a social gradient in health, and thus a social gradient in risk. At the same time, insurance contracts offered to individuals are often based on several criteria that categorize the population into several different segments. This initial categorization might capture all differences in socioeconomic status, as well as risk factors that are related to social status. If so, there will less likely exist differences in socioeconomic status within a segment, and unobserved risk factors that differ within that group of insurance takers are explained by other variables than social status.

As far as we can see, different insurance companies vary in their degrees of categorization based on observables today, varying from relatively rough categorization based on age and income to categories based on age, income, education and profession. Earlier arguments of the existence a social gradient in risk in health- and life-insurance supports the incentive for insurance companies to use variables related to social status, such as income, profession and education, for categorization. Probability of premature death and/or getting diseases also typically increases with age.

Even in the cases in which variables related to social status, such as income, education and profession, are used for categorization, we find it reasonable to assume that there will still exist differences in socioeconomic status within a segment. These differences can be related to other factors which are more intangible of nature, and thus unobservable for the insurance companies. Using similar argumentation we can also assume, on a general level, that there exists a social gradient in risk within these segments. We can imagine that some of individual risk is explained by differences in traditional measures of social status. The remaining unobservable risk factors can then be related to other aspects of social status as the ones mentioned above. Since we are considering a potentially very large amount of segments within the market it is possible that this contention is true in some cases, while false in others.

If the critera used for categorization are correlated with individual risk, we assume that the problems related to asymmetric information will be smaller the finer the categorization is. At the same time, we believe that the level of asymmetric information in health- and life-insurance can be further reduced if the insurance companies are able to collect other types of individual information that could explain the remaining unobserved risk factors. We know that the probability of e.g., premature deaths or probability of becoming disabled may also depend on actual behaviour. Some of the variables described so far may capture the behavioural dimension at a group level, but not at an individual level. We argue that some of the still unobserved risk factors that differ within a product segment could very possibly be related to differences in individual behaviour. Actual behaviour can again be related to social status. For example - being active, eating healthy and engaging in risky activities, are all activities that can to various degrees affect your health while at the same time being related to social status.

7.1.2 Exclusivity of Signalling

How we argue about exclusive opportunities to signal risk types in the health- and life-insurance market will, in similar ways as in the previous section, depend on the initial categorization. If there are no differences in SES within a segment, there will be no differences in the opportunity of signalling risk type. Nevertheless, we argued that we found it reasonable to assume that there will still exist differences in socioeconomic status within different segments. What we then have to consider, is the nature of the signalling which will be brought about by big data, and whether we believe that only certain types will be able to engage in it.

Thus, if we assume that individual behaviour, referring to previous section, is the main source to the remaining asymmetric information, we need to consider how insurance companies can use big data to effectively reduce this problem. Lets say that, in addition, to the initial categorization, the insurance takers are given an opportunity to purchase a health sensor which will collect behavioural information that is relevant for a person's health. The data is then shared with the insurance companies who use this information to make better estimations of an individual risk. In our framework, we can translate this to the opportunity for insurance takers to perfectly signal their risk type, and receive a new contract offer. The low risk types will thus have an incentive to purchase this sensor and signal that they are a low-risk type by sharing their behavioural data with the insurance companies.

On an overall level in the population of insurance takers, we can argue that individuals in the upper social strata will be more likely to have better opportunities to signal their risk type, due to advantages in relevant knowledge and for example better access to relevant technology. The question that arises is whether this type of signalling can be exclusive to the members of the relatively higher socioeconomic group within a segment. We find it more realistic to assume that individuals with a relatively higher SES are more likely to be able to signal their true risk type through the utilization of sensor technology. Thus, we can say that both exclusive or inclusive signalling will be relevant benchmarks, and that the most realistic scenario will lie somewhere in between the two.

7.1.3 Other Characteristics

Since we are assessing the private market for health- and life-insurance, we can first state that we are in a scenario close to that which uses non-linear contracts. In this case we have to consider the composition of insurance takers - does the life- and disability-insurance market have a small or large share of high risk types? The answer to this question is not necessarily straightforward.

Statistics from Finance Norway shows that there were 1,055,848 individual capital insurances in Norway in 2016. Of these, 604,158 were risk coverage of death and 268,760 were risk coverage of disability (Finance Norway, 2016). In comparison 40,727 Norwegians died in 2015 (Statistics Norway, 2016) and the number of people receiving disability benefits increased by 5,200 from third quarter 2016 to third quarter 2017 (NAV, 2017). Although these numbers are not directly comparable with each other, we conjecture that there are relatively few people that actually die or become disabled compared to the number of people purchasing this kind of insurance. We therefore argue that the private health- and life-insurance market consists of a relatively small share of high risk types.

We will continue by assuming that the share of high risk types is sufficiently small for there to not exist a separating equilibrium. Insurance companies will then initially offer a pooling contract to everyone in the respective segment of the population.

7.1.4 Predictions from Model

Finally, we can now use our framework to determine how we believe the low-SES individuals of the private health- and life-insurance market in Norway will be affected by the development of big data. Based on the characteristics described so far, we turn our attention to the scenarios and outcomes described in table 4.

A common understanding of better categorization of risks in the insurance market, is that the total insurance coverage will increase. More actuarially fair pricing of individuals will lead insurance takers in the direction of fully insuring themselves. If we consider the case of exclusive signalling, we find that this is not necessarily the outcome. In this case, the low-SES individuals may receive either a new pooling contract with a higher premium and less coverage than before, or a set of separating contracts where the high risks choose full insurance and the low risks must settle with less coverage than before. On the other hand, if signalling of risk type is available for everyone, we see that everyone will choose to fully insure themselves. In the market for private health- and life-insurance, we believe that the latter case is more plausible, and that the total coverage for low-SES individuals will rather increase than decrease.

The development of big data in the market for health- and life-insurance will ultimately reduce the problems of information asymmetry in the industry. As a result, more actuarially fair prices and higher total coverage is brought about, and we can say that the development of big data will make the market for health- and life-insurance more efficient. At the same time, this process will generate both winners and losers among the insurance takers. We expect that the small share of high-risk individuals will only be harmed, since they will lose some of the initial cross-subsidization and will have to pay a much higher premium than before. We expect that the larger share of low risks will generally be better off, but that there will be cases where they will face a higher negative discrimination due to their inability to signal their risk type. With this in mind, we argue that low-SES individuals will overall be worse off by the development of big data. Due to the existence of a social gradient in risk, a relatively larger share of high risks in the low-SES group loses their cross-subsidization. In addition, there is a possibility that some of the low risks in the low-SES group will not be able to signal their true risk type, and will thus have to face a larger burden of subsidizing the high risks.

Lastly, we have to discuss to what extent we believe low-SES individuals in Norway will be harmed. In Norway, private health- and life-insurance is supplied to individuals which typically finds the public supply of insurance not sufficient for their needs. Thus, everyone in the market is to some degree already insured, and guaranteed compensation in case of illness or loss. We can therefore argue that only a share of the population will actually be affected by the development of big data in the private health- and life-insurance market. In addition, as mentioned before, people with different education and profession are often already treated differently by insurance companies already. Better risk classification through big data can make this differentiation larger, but it will have a smaller impact than if there was not any initial classification. Another dimension of better risk classification, not captured by the model, is the possibility that high risks are not able to purchase private health- and life-insurance because it becomes to expensive. In a society where health insurance is to some degree provided publicly, the negative effects of these cases will be reduced. Thus, we believe that the impact of big data on low-SES individuals will be larger in other countries, where universal health care and other welfare benefits is of a lower quality.

7.2 Fairness Considerations

We have spent the preceding chapters making considerations of various effects big data may have on consumers. This has to a large extent been descriptive in nature. We now find it appropriate to assess policy implications of the outcomes we believe will arise as big data becomes increasingly integrated in the insurance sector. We structure this section as follows. We first present and comment on two tables that consider the prices that arise under perfect and exclusive signalling. In each table the price sets are compared to the optimal prices under egalitarian and efficiency-seeking fairness considerations. This forms the basis for our fairness considerations. We then make additional comments on fairness that is not directly captured by the efficiency-egalitarian consideration. Finally, we discuss the potential need for regulatory measures, as well as trade-offs that may arise.

In table 6 we show the outcome of big data in the case in which perfect categorization is achieved. We see that there consistently is a divergence from the average price, and an egalitarian planner would consider the pricing scheme as unjust, in that low-risk individuals are left better off than those of high risk. For the efficiency seeker, the pricing scheme corresponds perfectly to the actuarially fair price vector which she deems optimal. The efficiency seeker will thus be for the introduction of big data, while the egalitarian is likely to propose some form of redistributive policy.

Table 6: Fairness Considerations under Perfect Signalling

	Egalitarian		Outcome		Efficiency seeker
Low-SES, low-risk	$\bar{\alpha}$	$>$	α^{l*}	$=$	α^{l*}
Low-SES, high-risk	$\bar{\alpha}$	$<$	α^{h*}	$=$	α^{h*}
High-SES, low-risk	$\bar{\alpha}$	$>$	α^{l*}	$=$	α^{l*}
High-SES, high-risk	$\bar{\alpha}$	$<$	α^{h*}	$=$	α^{h*}

We then show in table 7 the prices that typically arise under exclusive signalling[23]. For neither of the social planners is the outcome unambiguously optimal. The egalitarian considers an unfairness in the sense that the high-SES, low-risk group is better off than all the other insurance takers. She will then propose a redistribution from the winners (high-SES, low-risk) to the remainder of the insurance segment. The efficiency seeker considers the pricing scheme scheme as unfair, in the sense that there is an inefficiency occurring by pooling the low-SES, low-risk insurance takers with the high risks. Increasing the ability for low-SES individuals will then be the solution to the unfairness as viewed by the efficiency seeker.

Table 7: Fairness Considerations under Exclusive Signalling

	Egalitarian		Outcome		Efficiency seeker
Low-SES, low-risk	$\bar{\alpha}$	$<$	α'	$>$	α^{l*}
Low-SES, high-risk	$\bar{\alpha}$	$<$	α'	$<$	α^{h*}
High-SES, low-risk	$\bar{\alpha}$	$>$	α^{l*}	$=$	α^{l*}
High-SES, high-risk	$\bar{\alpha}$	$<$	α'	$<$	α^{h*}

Note again that the two preceding tables, and indeed most of our arguments, depict scenarios extreme in nature. We do not consider that either perfect or exclusive signalling are likely situations to arise in the advent of big data. We rather expect that companies will be able to categorize their insurance takers better, in which some variables capture individuals regardless of SES, while others will be limited to categorizing only some people, and we believe the latter will be correlated with SES. Inasmuch as this is the case, a realistic prediction will be a mix of the two categorization scenarios we propose. This must be kept in mind as we make inference, but the presentation of extremes makes for a more intuitive understanding.

[23]We have in table 7 not included case iv) from table 3, in which all individuals are initially offered separating contracts with actuarially fair premia. Exclusive signalling will not change the contracts offered to the remaining risk pool, after the low risks in the high-SES group is uncovered. Since the outcome is actuarially fair premia, this scenario is more related to table 6 and the outcomes brought about by perfect signalling.

7.2.1 Other Aspects of Fairness

In the following, we discuss aspects of fairness and redistribution not directly inferred from our framework of fairness.

Related to the responsibility we impose on individuals, is the controllability of risk. Depending on how risk arises, that is; from immutable or controllable characteristics, considerations of fairness will be adjusted. We pose that much of the new categorization enabled is based on behavior, which arguably is controllable. This points towards an efficiency-seeking consideration of fairness. However, as we have mentioned, there may be immutable dispositions in individuals that enable them to control risk at a lower personal cost, indicating that egalitarian considerations are appropriate. We do not pose a specific view, but argue that both fairness views are legitimate, and need to be adapted to specific cases in which the controllability of risk can be specified to a higher degree.

Related to controllability of risk, we can quickly consider elements of exogeneity and endogeneity of SES. The degree to which high SES is achievable to anyone carries implications for how much we emphasize redistribution. We pose that two factors are relevant here; the degree of social mobility, and socioeconomic differences in a society. The first refers to how difficult it is to move along the social ladder, and will typically relate to mobility-promoting institutions, such as free education. The second refers to how tall the ladder is, and can be proxied by inequality indices such the Gini coefficient[24].

Another concept concerning redistribution is the concern for inefficiencies that may arise as a result of underinsuring. Though we are not able to model it, we can imagine cases in which underinsured individuals that are struck by an accident go bankrupt. In a welfare setting, these individuals will be put on some welfare program, perhaps financed through taxation at a higher price than redistribution would have had in the outset. This potential cost might have policy implications, as it has had in the health sector of many countries,

[24]The Gini coefficient is defined as half of the arithmetic average of the absolute differences between all pairs of incomes. This can be expressed as $G = 1 + \frac{1}{n} - \frac{2}{n^2\mu}(y^1 + 2y^2 + ... + ny^n)$ for $y^1 \geq y^2 \geq ... \geq y^n$, where y is people's income, μ is average income and n is number of income recipients (Barr, 2012).

bringing in a public health care system.

On a related note, equal prices will lead to problems of adverse selection, typically causing low-risk individuals to underinsure themselves. In the case of actuarially fair prices, our model indicates that all insurance takers will be lead to fully insure themselves. On the other hand, not captured by our model, we can imagine that if high-risk individuals are priced according to their actual risk, the implication will be that some of the high-risk individuals are no longer able to purchase insurance at all. If we in addition consider that there exists a social gradient in risk, this could imply that it is more likely individuals of lower socioeconomic status that are unable to insure themselves.

Another form of inefficiency that we do not capture, is related to the cost of redistribution. In its simplest form, we consider that redistribution happens without a cost, though there is usually some value lost in the transaction. The social planner will need to take this efficiency aspect into consideration.

In the scenarios we deem plausible post big data, the efficiency-seeker will never suggest redistribution of wealth. On the other hand, the egalitarian will consider aspects related to controllability of risk and innefficiencies of underinsuring, and will suggest redistributory interventions from low risks to high risks. If there exists a social gradient in risk, this implies that high-SES individuals to an extent will be obliged by the egalitarian to transfer their wealth to low-SES individuals.

7.3 Methodological Concerns

We will in this section highlight potential methodological problems that may cause problems for our analysis. We will discuss the realism of different assumptions and simplifications we have done in our framework. In addition, we will specify in what ways relaxing our assumptions will potentially affect our analysis.

7.3.1 Single-crossing Assumption

An important assumption in our methodology is that probability of loss is the only factor that differentiates the demand for insurance across types. This implies an assumption that socioeconomic status has no effect on demand, after an insurance segment has been grouped together. This means that all observable variables that insurance companies use have been taken into account, and are equal for both types of SES. We are then left to consider the effect of unobservables in SES[25] on demand for insurance.

We can first consider the implications of the assumption not holding. Smart (2000) studies a competitive insurance market in which insurance takers differ with respect to both accident probability and degree of risk aversion. His analysis suggests that the features of eligible equilibria are changed in significant ways. Although risk aversion is irrelevant to insurers in terms of costs, it introduces "noise" into the problem of inferring insurance takers' type from observed actions (Smart, 2000). Similarly, Wambach (2000) finds that in cases in which the single-crossing assumption does not hold, equilibria may exist at which firms make positive profits with separating contracts, as well as other cases that differ from the RS-equilibrium.

Further, we need to assess the conditions under which the single crossing assumption holds. First, we claim that if an effect of (unobservable) SES on demand exists, its direction is ambiguous. On the one hand, if lower SES is associated with low material wealth, this will imply larger risk aversion for low-SES individuals under an assumption of decreasing absolute risk aversion[26]. Similarly, it is reasonable to assume that higher SES entails more sources of alternative insurance, e.g., through family's wealth, making conventional insurance less necessary. On the other hand, for some cases it may be reasonable to expect that low SES comes with a restriction of resources, inhibiting individuals from taking the optimal amount of insurance. These barriers from taking up insurance need not be

[25] Note that unobservables not correlated with the social stratum cancel out on average if the insurance segment is large enough.

[26] We consider this a reasonable assumption, and find that Wambach (2000) models insurance takers' risk aversion to behave as such.

economical, but can be informational, limiting knowledge of insurance possibilities.

In the case in which low SES is associated with increased demand for insurance, we can use arguments analogous to Wambach (2000), who considers the additional dimension of wealth in the Rothschild-Stiglitz model. We know that $MRS^{hH} < MRS^{lH}$ and consider the case in which $MRS^{hH} \leq MRS^{lL}$. If the effect of SES on demand for insurance is not too strong, this will be the case, and the equilibrium holds as before, pooling SES-types together. Wambach considers cases in which the inequality does not hold, and finds that conditions for equilibrium depend on the relative proportion of agents. Some of these cases may be relevant, but we find it to be outside the scope of this thesis. We also believe that similar results will arise in the case in which demand for insurance increases with SES.

As such, if we believe that insurance takers, apart from loss probability, are homogeneous to a satisfactory degree in their demand for insurance, our results should hold. In contrast to many papers on insurance, we analyze fairly narrow segments of insurance takers (as they are considered post-categorization), and we believe that this in some ways make them relatively similar in tastes, despite the differences in privilege that may allow for social gradients and exclusive signalling. Thus, we believe our results hold.

7.3.2 Perfect Signalling

We have modeled big data as an observation of insurance takers' signals of risk type. We have simplified our analysis by considering the case in which signalling of risk type is perfect. In other words, we assume that individuals are enabled to signal their true risk type without a cost, and no possibility of signalling the wrong type.

We can relate the quality of signalling to the cost of signalling and the opportunity of signalling the true risk type. We have argued that big data may lead to a utilization of new data sources, capturing the behavioural dimension of an individual's risk profile to a larger extent than before. However, if the cost of engaging in these activities is similar for both risk types, high risks would also begin to engage in these activities to avoid being classified as high risk. The quality of the signal will then be poor since both risk types are able to send it, and eventually there may not exist any correlation between these activities and risk type anymore; a case of Goodhart's law, as described in our section for Weaknesses of Big Data (3.2).

Nevertheless, we find it reasonable to believe that there will often exists some differences in cost of engaging in risk correlated activities. The signal will therefore be associated with some informational value, but it is imperfect in the sense that there might be cases in which low risks fail to signal that they are low risk, and high risks may be able to falsely signal that they are low risk. Imperfect signalling of risk is considered in our section for Exogenous Categorization of Risk (4.3.1). Schmalensee (1984) and Hoy and Lambert (2000) shows that implications of imperfect signalling is typically that prices, on average, will better reflect an individual's expected cost. On the other hand, those who are misclassified will face a larger price-cost differentials than before.

7.3.3 Exclusive Signalling

We have in this paper argued that people with higher socioeconomic status may be privileged, in the sense that they have opportunities that are exclusive to them. In our model we illustrate this exclusivity by assuming that *only* people of high socioeconomic status are able to signal their actual risk type to the insurance companies. We have previously argued that it might be more realistic to assume that, rather than having a clear cutoff for exclusivity, the probability of being able to signal their risk type *increases* with socioeconomic status. In other words, we can imagine that a more realistic approach would be to relax this assumption and instead include a kind of social gradient in opportunities.

For illustrating purposes we find the assumption of exclusive signalling reasonable. A relaxing of this assumption will surely give more precise results, but it will not bring any new implications to our model.

7.3.4 Endogenous Risk types

We have modelled individual risk as being exogenously given. This risk can be interpreted as springing from a mix of immutable characteristics and behaviour. However, we have argued that the increased use of big data can incentivize insurance takers to behave in less risky ways. Thus, a natural extension of our model may be to design risk as an endogenous variable, which may change from the pre big-data situation to the post big-data state, shifting some insurance takers from high to low risk. Combining this with imperfect signalling would likely increase the precision of our model.

7.3.5 Risk Categorization and Privilege

A comment on the assumed behaviour of insurance companies is in order. On the whole, we consider that an insurance segment as illustrated in the Model section (6.1) is considered after all relevant observable factors are taken into account. By "relevant", we mean factors that are correlated with the riskiness of an insurance taker, and expect that these correlations are often imperfect. We note that there may be cases in which observables will not be correlated with risk, especially when multiple variables are used by the insurance company. Consider income, which may lose it's correlation when we correct for other variables, such as education and profession. If this is the case, insurance companies will not discriminate on income.

Two implications spring out from this. First, the single-crossing assumption may be less likely to hold, as discussed earlier in this chapter. Second, the exclusivity in signalling may be affected. Despite wealth losing its correlation with risk, it may still be significant in affecting an individual's privilege in signalling risk types.

7.3.6 Equilibrium Concepts

In our paper we have only considered the equilibrium concepts by Rothschild and Stiglitz (1976) and Wilson (1977). However, there exists several concepts of equilibria and proposed solutions to the "equilibrium-non-existence"-debate. In this section we follow the summary by Rees and Wambach (2008), and give a short description of different concepts that could also be considered in our framework.

One equilibrium concept was introduced by Riley (1979). In the Wilson concept insurers anticipate that other insurers will withdraw contracts as a result of their deviation. Riley goes one step further and assumes that deviating insurers anticipate that at least one other insurer will react by offering an additional contract. If the RS contracts are initially offered, insurers shy away from offering deviating contracts as they anticipate that it will make a loss once other insurers have reacted to the deviation with a new offer; If an insurer were to offer a deviating pooling contract, then due to the single crossing property another insurer can offer a contract which just attracts the low risks. Thus the deviating insurer is stuck with the high risks and makes a loss. Thus, the RS separating contracts is an equilibrium even if there are only a few high risks in the market.

Based on Wilson (1977), Miyazaki (1977) and Spence (1978) have extended the analysis to contract menus and show that the anticipatory equilibrium concept results in an allocation with separating contracts. This equilibrium concept is commonly referred to as the Wilson-Miyazaki-Spence (WMS) contracts. The equilibrium is the solution to the following maximization problem; The utility of the low risks is maximized under two constraints; the incentive constraint and the participation constraint. The incentive constraint assures that the high risks must weakly prefer their intended contract over the alternative, and the participation constraint ensures that the insurance companies make non-negative profits overall. An interesting aspect of the WMS equilibrium is that insurance companies may offer different kinds of separating contracts with varying degrees of cross-subsidization, which jointly make non-negative profits. In contrast, the RS separating contracts is of the no-subsidy type[27].

Lastly, so far we have considered only equilibra in pure strategies. Dasgupta and Maskin (1986) have shown that an equilibrium in mixed strategies exists if the RS contracts do not constitute an equilibrium. In this context, mixed strategies mean that each insurer offers different sets of two contracts, each with some probability. The interpretation is that insurance companies should randomize contracts offered to different groups of individuals. We find this concept unintuitive, and we will thus not describe it in any more details, nor do we find it necessary to be considered in our framework.

The concepts of Wilson, WMS and Riley, include some form of dynamics, namely the possible reaction of insurance companies after the new contracts is offered. We find it useful in our analysis of the insurance market to assume some foresight of the insurance companies. If we adopted the Riley concept, we would ensure the existence of an equilibrium. The disadvantage is that we would only consider the RS separating contracts in our analysis. We believe that it is reasonable to assume that there exists contracts that include cross-subsidization in the insurance market. Thus, we argue that the Wilson concept is a better alternative than the Riley concept. We note that the WMS concept includes both foresight and the opportunity to use separating contracts of the subsidy type, and thus could be relevant to implement in this analysis. Due to the nature of this paper, we have not considered this case, but we conclude that the combination of the Rothschild and Stiglitz and Wilson is sufficient to answer our research question.

7.4 Other Considerations

The impact big data will have on the insurance market is all but clear. We have modelled the impact as an ability to better categorize (some) insurance takers. This categorization is still based on pooling risk, and placing individuals into the correct pool. Another effect of more information is that we create more risk pools. There may exist cases in

[27]It can be shown that the RS separating contracts can be one extreme example of a WMS equilibrium, in which there is no cross-subsidization between the separating contracts (Rees & Wambach, 2008).

which these risk pools become increasingly small, so that these market for insurance essentially fall apart. We can relate this extreme scenario to a situation with a continuum of risk probabilities, rather than a discrete distribution. Rothschild and Stiglitz (1976) conjectured that a stable equilibrium was unlikely to occur for the case of a continuum of risk classes, and this conjecture was proven by Riley (1975). This result holds for static expecations. We are not able to provide results under revised expectations. However, we can argue that the more information we have, the less willing we are to be grouped with more risky individuals, and the fortunate need to subsidize the unfortunate for insurance to function. As such, there may be a necessity for political forces to involve themselves in the insurance market.

8 Conclusion

To answer our research question, we have considered the utility of heterogeneous insurance takers in two states; pre- and post- big data. The distinction between the states is that the latter is characterized by increased opportunities for companies to classify insurance takers' risk profiles. The interpretation of this information is that insurance takers are enabled to signal their risk type due to information flows that arise from big-data models. The outcome of interest here is the change in utility for insurance takers with low socioeconomic status.

Our results indicate that the insurance market will on an overall level benefit from the development of big data. Less information asymmetry will reduce market inefficiencies related to the problem of adverse selection, causing low-risk individuals to underinsure themselves because they are priced too highly. More actuarially fair pricing of individuals will lead insurance takers in the direction of fully insuring themselves, increasing total coverage in the market. At the same time, we find that this development creates both winners and losers. Insurance companies will become better at separating customers varying in risk, and differentiate the contracts offered to different types. Low-risk individuals typically benefit from this in contrast to high-risk individuals, who are at best unaffected. Further, we include a social dimension in which insurance takers are able to vary in socioeconomic status as well as their risk type. We consider that people of lower socioeconomic status may be more likely to be of high risk, and that they may be less likely to be able to signal their risk type to insurance companies through the utilization of big data. We find in our model that the general tendency for changes in overall welfare for the low-SES group, consisting of both low risks and high risks, is one of adversity. The low-SES group will be harmed by either losing some of the initial cross-subsidization from the high-SES group or through inability of signalling their risk type, or through a combination of both.

In addition to assessing the utility changes for different groups when transitioning between the two states, we perform the aggregate outcome that arises in the post big data state. This analysis is based on two normative stances that reflect the trade-off between efficiency and egalitarian concerns, and relate to what a social planner may consider as fair.

Dependent on the extent of how big data enables signalling of risk type, and how the social planner weighs efficiency against equality, different policy implications arise. The efficiency seeker will suggest policy that allows insurance companies to categorize as precisely as possible. In the case where big data allows for perfect categorization, the efficiency-seeker will consider it optimal, and will not suggest intervention. In all the scenarios we deem plausible post big data, the egalitarian will suggest redistributory interventions, from low-risks to high-risks. If there exists a social gradient in risk, this implies that high-SES individuals to an extent will be obliged by the egalitarian to transfer wealth to low-SES individuals.

In addition to our theoretical approach, we describe the effects big data is expected to have on the insurance sector. Despite apparent efficiency gains that big data will bring about, we find it necessary to describe other aspects of big data. These include concerns related to use and interpretation of data, redlining and privacy. The development of big data calls for discussion on its wider effects, and regulatory concerns are likely to arise.

We see that such discussions are already taking place, as exemplified by the GDPR.

Throughout the writing of this thesis, we have shed light upon ways in which the development of big data may have impacts that can be considered undesirable, either seen from an individual's point of view, or from that of a social planner. We consider that in the midst of all the efficiency gains from big data, a discussion surrounding the adversity that may arise is in order. With this thesis, we hope to have contributed in a way that inspires further research on big data's wider impact on society.

Appendix

A Perfect signalling of SES

We here consider the case where insurance takers are not able to signal their risk type, but rather their socioeconomic status. We will not consider any case of exclusivity in this setting. Perfect signalling of SES will only cause the insurance companies to categorize their insurance takers into two different segments which is treated separately. In addition, we will not consider the case where there is no social gradient in risk. If there is no differences in the risk composition between the low-SES and the high-SES group, they will not be treated differently if they are separated. Earlier we have assumed that insurance companies knows the total share of low-risk and high-risk individuals in the population. A necessary assumption now is that insurance companies knows the total share of low-risk and high-risk individuals within each socioeconomic group.

A.1 Mandatory Insurance

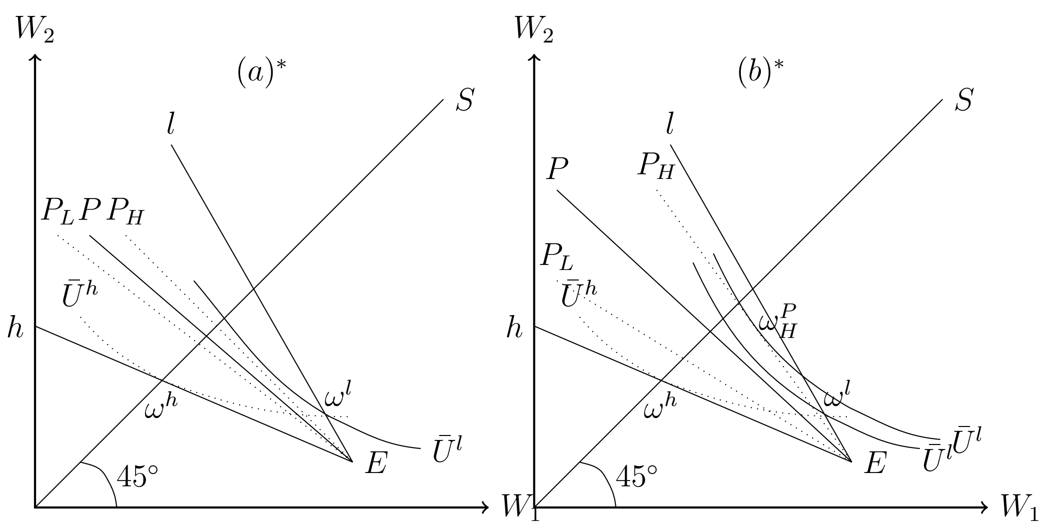
Perfect signalling of SES-type will make it possible for the insurance companies to treat the two groups differently. The average premium charged to the low-SES group will be $\bar{\alpha}^L = \bar{p}^L D$, and the average premium charged to the high-SES group will be $\bar{\alpha}^H = \bar{p}^H D$ [28]. When there is a social gradient in risk we see that $\bar{\alpha}^L > \bar{\alpha} > \bar{\alpha}^H$. In other words, perfect signalling of SES-type will remove the intial subsidization of Low-SES by the high-SES. The low-SES will be worse off and the high-SES group will be better off. Within each group the high risks will still be subsidized by the low risks.

[28] $\bar{\alpha}^L = \frac{t_L}{\theta}\alpha^{l*} + \frac{(\theta - t_L)}{\theta}\alpha^{h*} = \frac{t_L}{\theta}p^l D + \frac{(\theta - t_L)}{\theta}p^h D = (\frac{t_L}{\theta}p^l + \frac{(\theta - t_L)}{\theta}p^h)D = \bar{p}^L D$ and $\bar{\alpha}^H = \frac{t_H}{1-\theta}\alpha^{l*} + \frac{(1-\theta-t_H)}{1-\theta}\alpha^{h*} = \frac{t_H}{1-\theta}p^l D + \frac{(1-\theta-t_H)}{1-\theta}p^h D = (\frac{t_H}{1-\theta}p^l + \frac{(1-\theta-t_H)}{1-\theta}p^h)D = \bar{p}^H D$, where $\alpha^{i*} = p^i D$ is the actuarially fair premium for risk type i.

A.2 Non-linear Contracts

In the case of non-linear contracts, perfect signalling of SES-type will have different scenarios depending on the composition of risk in the population, as well as the magnitude of the social gradient in risk.

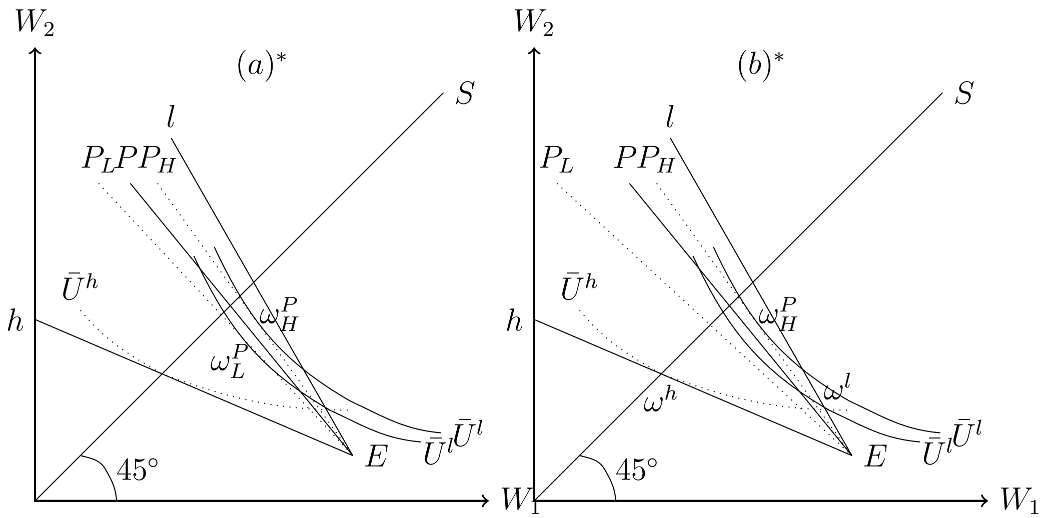
First, we can consider the case in which the total share of high risk types in the population is sufficiently large for there to exist a RS separating equilibrium. This situation is depicted in figure 12 with the set of separating contracts (ω^h, ω^l) which is initially offered to everyone. We can illustrate perfect signalling of SES-type by going from considering a pooled zero-profit line $(\overline{EP})$ for the whole population, to two different pooled zero-profit lines, $(\overline{EP_L})$ and $(\overline{EP_H})$, for the low-SES group and the high-SES group respectively. If we introduce perfect signalling of SES-type, the low-SES group will always be unaffected. The high-SES group will potentially receive a pooling contract (ω_H^P) in stead of the initial separating contracts, making everyone in that group better off. This situation is depicted in figure 17 (b). This holds If the social gradient in risk is sufficiently large; i.e., if the share of high risks in the low-SES group is much larger than the share of high risks in the high-SES group.



* (a) Separating(low-SES) and Separating(high-SES)
* (b) Separating(low-SES) and Pooling(high-SES)

Figure 17: Large share of high risks and Signalling of SES

Second, we can consider the case in which there is a small share of high risk types in the population, and the insurance companies initially offers a pooling contract to everyone. This situation is depicted in figure 13 with the pooling contract ω^P which is offered to everyone. If we introduce perfect signalling of SES-type, the low-SES group will always be worse off, as depicted in figure 18. They will either receive a new pooling contract ω_L^P with a higher premium and less coverage than before, or a set of separating contracts (ω^h, ω^l), depending on the degree of social gradient in risk. The high-SES group will always be better off, receiving a new pooling contract ω_H^P with a lower premium and more coverage than before.



* (a) Pooling(low-SES) and Pooling(high-SES)
* (b) Separating(low-SES) and Pooling(high-SES)

Figure 18: Small share of high risks and Signalling of SES

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List of Figures

List of Tables