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Theme issue contribution

From Actuarial to Behavioural Valuation. The impact of telematics on motor insurance

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Abstract

Algorithmic predictions are used in insurance to assess the risk exposure of potential customers. This article examines the impact of digital tools on the field of motor insurance, where telematics devices produce data about policyholders' driving styles. The individual's resulting behavioural score is combined with their actuarial score to determine the price of the policy or additional incentives. Current experimentation is moving in the direction of proactivity: instead of waiting for a claim to arise, insurance companies engage in coaching and other interventions to mitigate risk. The article explores the potential consequences of these practices on the social function of insurance, which makes risks bearable by socialising them over a pool of insured individuals. The introduction of behavioural variables and the corresponding idea of fairness could instead isolate individuals in their exposure to risk and affect their attitude towards future initiatives.

Keywords: adverse selection; behavioural valuation; telematics motor insurance; algorithmic prediction; subsidisation; risk transfer

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Introduction

Predictive algorithms are now so commonplace that, for many observers, they have become "an integral part of everyday life" (Kirkpatrick 2016: 16). These algorithms process data that refer to the past, but their purpose is to manage the uncertainty that refers to the future. That uncertainty becomes particularly significant when decisions have to be made that may cover such issues as the weather, stock prices or the movement of goods and people.

Referring to people, data mining algorithms are used to rate and score individuals on the basis of such questions as: who is more likely to regularly pay the instalments of a debt? Who is more likely to reoffend if he or she is paroled? Who is more likely to efficiently perform the tasks required by a firm? Much research has already demonstrated that predictive algorithms can be extremely useful in all such cases, as they offer decision makers a presumably fail-safe way to measure the risk of backing the wrong person (Provost and Fawcett 2013). That is why predictive algorithms are already used, for example, in hiring and recruiting decisions (Miller 2015; O'Neil 2016: ch. 6), in peer-to-peer lending (Biferali 2018) and in parole procedures (Harcourt 2006).[1]

Our aim in this article is to address another sector where the possibility of using predictive algorithms to evaluate individuals is attracting much attention and, in recent years, also major investments: insurance. The issue here has traditionally been one of how to evaluate individuals to be insured in such a way that any compensation payments that the company might have to make in future do not exceed premiums received in the past. Ironically, insurance companies would prefer to insure only those individuals who do *not* need insurance, i.e. those who will not claim. Because nobody can foresee the future, however, insurance companies strive to improve their selection of prospective policyholders so that the percentage of high-risk individuals in the pool is not disproportionate. When insurance companies fail to do this, they are confronted with the problem of adverse selection. The number of bad cases is too large compared to the number of good cases, and the loss ratio (i.e. the ratio of losses to premiums earned) deteriorates. Adverse selection is often a consequence of information asymmetry (Stiglitz 1983).[2] Policyholders

[1] Giving rise to problems of bias and discrimination, involving both the design of the algorithms and the data used. Both issues have been discussed at length in the relevant literature. See, for example, boyd and Crawford (2012); Gitelman (2013); Gillespie (2014); Pasquale (2015); O'Neil (2016).

[2] Literature on adverse selection is very great. An important contribution on this topic is Baker (2003), where adverse selection is investigated as a "dual problem" (selection can be adverse either to the insurance company or to the prospective policyholders) with pooling and de-pooling effects.

usually have more information about their actual exposure to danger than they are willing to disclose to an insurance company – either because they fear they would have to pay a higher premium, or because they fear the company could refuse coverage. This asymmetry also affects competitiveness: companies which better reduce information asymmetry, that is, whose percentage of high-risk individuals is not disproportionate, are better placed on the market. For insurance companies it is therefore extremely important to get as much information as possible, in order to improve their evaluation of prospective customers and to minimise adverse selection.

This is one of the reasons why they are adopting new forms of valuation, using algorithmic procedures to estimate the risk probability of individuals according to their actual behaviour. By means of monitoring and tracking devices, insurance companies can resort not only to more information but also to different information, namely, information about individual behaviour. This form of *behavioural valuation* promises to reverse the asymmetry: insurance companies might have more information than the customers themselves about their actual risk profile (Cevolini and Esposito 2020).

Recent techniques based on machine learning and using big data promise today to deliver reliable targeted predictions that refer to single individuals (Domingos 2015; Siegel 2016).[3] This possibility, if it could be implemented in practice, would be particularly well suited to guiding the valuation and selection routines of insurance companies. Digital technologies are expected to impact not only on pricing, but also on the entire value chain of the insurance industry (Eckert and Osterrieder 2020; Eling and Kraft 2020; Eling and Lehmann 2020), with potentially disruptive effects (Boobier 2016; Braun and Schreiber 2017; Albrecher et al. 2019). However, it has been observed that academic research on digitisation in the insurance industry is still quite scarce (Cather 2018; Eling and Lehmann 2020). Our investigation addresses current experimentation in this field, also with the goal of contributing to plugging the current gap in academic research.

We focus on the sector of third-party liability motor insurance because it is one where behaviour-based pricing is most advanced, in terms of both technological experimentation and concrete insurance practices. While giving due consideration to the huge and varied panorama of telematics third-party liability policies currently available worldwide, we focus in particular on the telematics policies offered by a selection of Italian insurance companies. The reason for this choice is that Italy was an early adopter of digital technologies for evaluating driving behaviour and is also still a cutting-edge country in developing

[3] For a critical analysis of the many controversial sides of these technologies, see, for example, Rona-Tas (2020).

motor insurance telematics from a legal and regulatory standpoint (Dang 2017).

The topic is very complex and, in part, also controversial (McFall et al. 2020). Some researchers have expressed doubts about what is often presented as one of the most revolutionary innovations in the digital valuation of insured parties, i.e. the possibility of customising policy premium. For Liz McFall and Liz Moor (2018: 205), it is too early to say that premiums are "tailored" to individual policyholders in connected insurance. This would mean that the feared hyper-individualisation of premiums (Billot et al. 2018) leading to a drastic revision of the traditional models of risk-sharing is still no more than a hypothesis, rather than reality in insurance practice. For Maiju Tanninen (2020: 8), empirical research shows that the utopian (or dystopian?) idea of personalised insurance "is not very easy to achieve", even though one cannot rule out that behaviour-based insurance is able to explore "alternative imaginings" for adapting policy premiums to individual risk exposure. In a recent study of telematics motor insurance, Laurence Barry and Arthur Charpentier (2020) reached the conclusion that, with regard to pricing and tarification practices based on assessment of the policyholder's exposure to the risk insured, "nothing revolutionary has happened yet" (7) and the expected disruption of the insurance industry "actually did not happen" (6).

Our research explores and questions these conclusions. Is there really nothing new in the use of digital technologies to assess risk exposure in motor insurance? Barry and Charpentier (2020: 7) themselves admit that the addition of behavioural variables to classical actuarial statistical variables "is itself *radically new*" (emphasis added). Our study further investigates this novelty. We use the current literature about telematics motor insurance as a starting point for empirical research in which we set out to understand what is really happening in insurance companies that sell telematics products,[4] with possible consequences also on the social role of insurance. In this article we present the first results of this research. We explore three different aspects of the impact of telematics-based techniques on insurance: challenges to business models and calculations of insurance companies (in the third section), challenges to the relationship between insurance providers and policyholders (fourth section), issues about fairness and discrimination (fifth section).

Looking inside an insurance company is notoriously difficult. To gather empirical material, we conducted semi-structured interviews

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[4] Research conducted by Barry and Charpentier is based on a review of articles published about UBI and telematics motor insurance over the last decade, presented as "an exploratory analysis of documents" (6). The two researchers are aware of the fact that the articles they considered do not necessarily "reflect the actual practices of all insurers" (9).

using two questionnaires: one, more sociological, was aimed primarily at companies offering telematics third-party liability motor insurance; the other, more technical and actuarial, was aimed at the software providers, data scientists and mathematicians who analyse the data and the problems deriving from extracting information for predictive purposes. We interviewed three executives of Italian insurance companies, one actuarial mathematician of an Italian insurance company, three heads of data analytics of international software providers. An Italian executive with past experience as an actuarial mathematician answered both questionnaires.

The names of the interviewees and of the companies were anonymised by using capital letters for the companies and numbers for the interviewees (interview A.1, B.1 … and A.2, B.2 … when two or more people of the same company were interviewed). Because interviews were conducted between autumn 2020 and spring 2021, during the pandemic emergency caused by COVID-19, we opted for digital meetings. The interviews, which lasted 60 to 90 minutes, were conducted either in Italian or English by one of the authors, were recorded, transcribed and then carefully analysed and cross-commented by both authors.

Our interviews cover three of the four insurance companies which offer a telematics policy.[5] Respondents showed a striking uniformity in jargon, core issues, technical problems and digital solutions. The differences lie rather in the amount of data available and the purpose for which it is used. Apparently no one has the Coca Cola formula in its safe. Our interviewees also shared their expertise far beyond the concrete limits of their company practice, covering their knowledge of competitors and of the current experimentation in the field.

The results we have derived from our interviews so far confirm that the practice does not correspond to the often very emphatic narrative that accompanies digitalisation of the insurance industry.[6] Rather, our investigation of actual practices enabled us to identify some more subtle issues and important changes in the motor insurance sector, from which indications can be drawn for the evolution of insurance in general. The trends we observe might have an impact on the basic assumptions of insurance and on its social significance, thus introducing genuine though less emphatic novelties.

In this article, we present some of these issues and changes. At this stage we only explore the perspectives of insurers, software providers and data scientists, trying to get an insight into current innovations and their relevance to the field. Our knowledge of policyholders and

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[5] Unfortunately, the company with the highest number of telematics policies declined to answer our questionnaires.

[6] Barry and Charpentier (2020: 2) talk about "myths […] associated to predictive analytics".

their attitude relies only on the way insurers observe subscribers of telematics third-party liability motor insurance policies. Further research might fill this gap, addressing directly a user's perspective.

In order to understand the impact of digital technologies on the assessment of policyholders' risk exposure, we first have to clarify how the insurance industry implements its risk management mechanism.[7] We present this preliminary clarification in the following section.

Subsidisation vs risk transfer

Insurance is a form of socialisation of risks, which generates specific financial solidarity between policyholders. The mechanism on which insurance business is based is usually described as "risk pooling and spreading". The underlying idea, which reproduces the primary insight of probabilistic calculation, is that while in terms of the individual the risk is in principle unpredictable, in terms of the group the aggregation of many individual risks generates reliable regularities that provide a basis for calculation. By pooling risks, in other terms, "*accidents* become *normal,* and in that sense not accidents at all" (Ericson et al. 2003: 47, emphasis added). So statistics offer the insurance industry a sort of "secondary normality" (Luhmann 1991: 1) that can be managed by means of calculation and the availability of sufficient data, giving the impression of controlling the unpredictability of the future.

For the insurance industry, risk pooling is an essential tool for transforming an unmanageable risk into a bearable one. From the viewpoint of an insurance company, the advantage of accepting a multiplicity of similar cases lies in the possibility of using good risks to compensate for bad ones: those who pay the premium but do not claim should offset[8] those who pay the premium but suffer damage (e.g. a car accident) for which they can then claim compensation. All these policyholders are members of a pool, prepared to pay an often fruitless premium in exchange for the certainty of compensation if they suffer the damage in question. That is how the financial risk is spread between all policyholders.

The risk is compensated by sharing it not only socially, between various policyholders, but also temporally, between various moments in time (Albrecht 1992; Farny 1995). As a result, premiums accumulated in the course of time are used to reimburse the unluckier cases when they occur. The uncertainty at play thus concerns not only *who* may be affected by misfortune, but also *when*. These two

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[7] In this article we focus on ongoing insurance practice concerning actuarial valuation. Alternative uses of digital technologies in the insurance industry are of course possible.

[8] Or, "ristorano", as Benedetto Cotrugli already expressed it in the mid-fifteenth century (1602 [orig. ed. 1458]: 75).

dimensions of uncertainty – the social and the temporal – interact with each other, enormously increasing the complexity of the situation that the insurer has to tackle. The ingenious thing about the insurance mechanism is that it transforms this problem into a solution: pooling risks is a way of spreading risks between the members of the pool over the course of time, thus guaranteeing financial solidarity between all those who decide to take part by paying the premium. In this sense, "insurance is the paradigmatic risk-spreading institution" of modern society (Baker and Simon 2002b: 7). That said, however, solidarity between policyholders can take two different forms, with different social implications: *subsidiarity*, or *risk transfer*. We deal with them in this section of the paper.

If we follow the explanation of the insurance mechanism presented above, it must be admitted that policyholders who pay their insurance premiums are not paying it *for themselves*. Instead, by paying their premiums, they join what could be described as a "secondary collectivity", whose members are all those who have decided to pool their fate, in financial terms and with certain conditions. For the company, the only important thing is that, at the end of the predetermined period, total losses have been covered by the premiums collected from all policyholders who joined the group. In other words, there must be an "equivalence" between what the company collected in advance on the basis of its own estimates about future claims (in terms not just of frequency, but also of severity) and what the company will have actually paid in terms of compensation when the future will have become the past (Mahr 1951; Farny 1992). If the principle that governs calculation of the pure premium (i.e. the spreading of risk) is that of homogeneity, then the financial solidarity created among policyholders is termed *subsidiarity* (Thiery and Van Schoubroeck 2006; Lehtonen and Liukko 2011). What drives individuals to pool their fates under these conditions is essentially the uncertainty about who will be stricken by adverse fortune.

However, insurance companies know very well that not all individuals are exposed to the same degree of risk. In third-party liability motor insurance, for example, male drivers are statistically more exposed than females (whatever the reason may be) and those who have just passed their driving test are usually more exposed than mature drivers (presumably because they are less expert). It is therefore in the company's interest to introduce statistical differences, i.e. such variables as the driver's gender, age and place of residence, the type of car driven and so on, that enable segments to be created, with which a more accurate estimate of each segment's degree of risk exposure can be associated, so that the company can reach a more precise estimate of its corresponding expected loss. The company then employs this *segmentation* to elaborate a differentiated tarification that is updated continuously on the basis of historical claim data.

The most extreme form of solidarity emerging from *segmentation* has also been defined "chance solidarity".[9] By that, scholars mean that all members of a particular segment share exactly the same probability of filing a claim, and who will be the misfortunate one is simply decided by chance. Risk is spread among members of the same segment but not between members of different segments. From the viewpoint of a segment, this type of solidarity can be regarded as fair. From the viewpoint of a subsidising society, this type of solidarity can instead be regarded as unwillingness to help the underprivileged (Lehtonen and Liukko 2011).

The underlying principle of segmentation favours a different conception of the insurance mechanism, closer to the concept of *risk transfer.* The basic idea here is that every policyholder (or every predefined group of policyholders) transfers a particular risk to the insurance company and that, as a consequence, it is right that every policyholder (or, every predefined group of policyholders) pays in proportion to the risk thus transferred.[10]

An insurance company that opts for subsidiary solidarity misses out on the opportunity of being more competitive. By drawing distinctions between the different extents to which members of the pool are exposed to risk, the company could create separate segments and calculate a premium corresponding to each of them. Those who are less exposed to the risk would pay less and would thus be more attracted by the policies offered by the company practising segmentation than by the one that opts for subsidiarity.[11] The

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[9] See the seminal paper by De Wit and Van Eeghen (1984). Cf. also Lehtonen and Liukko (2011); Barry and Charpentier (2020).

[10] Both subsidiarity and risk transfer have pro- and contra moral justification (Baker 2003). Subsidiarity – simple risk pooling and spreading practised without the introduction of any particular differences – apparently has the advantage of eliminating all forms of direct discrimination: young drivers pay exactly the same as seniors, women pay the same as men, etc. But it also has many defects. It may be considered unfair by those policyholders who take more precautions, or who are normally more prudent, or in general believe that they are less exposed to risk. In addition to this, it is not in the company's interest to neglect these differences, for reasons that are both technical and economic.

[11] In addition, the insurance company could reduce adverse selection and make more accurate estimates about expected losses in each of the individual segments. When segmentation is practised on the basis of differences correlated statistically to claims causing an actual loss for the company, the use of these differences is considered legitimate by Italian law on the basis of the argument that renouncing this correlation would undermine the actuarial structure of insurance business and, in extreme cases, would make coverage itself impossible.

terminology used to describe this kind of discrimination is "actuarial fairness".[12]

Sociological research has demonstrated the existence of a trend in the last century towards growing opposition to subsidisation and an increasing preference for segmentation. Around the middle of the twentieth century, this trend triggered a sort of "spiral of segmentation", inspired by the desire to adapt the premium as far as possible to individual hazard (Barry 2020: 175). Of two distinct forms of self-understanding of the insurance mechanism – insurance as a form of subsidisation, and insurance as a form of risk transfer – the latter gradually took hold, generating an increasingly marked subsidy-aversion argument. It could be said that the individual's point of view has taken over progressively from the point of view of the group. The development of behavioural tariffs based on telematic data in the third-party liability sector of motor insurance, which we shall discuss in the next section, can be seen as part of this trend toward individualisation. However, behavioural individualisation cannot be reduced to the principle of increasing segmentation leading to ever narrower groups. For the insurance company the matter is rather to identify which individuals belonging to a certain segment will probably perform better and which individuals will probably perform worse.

Digital valuation of the degree to which policyholders are exposed to the risk indeed offers a unique opportunity to boost the practice of insurance as a form of risk transfer, with a series of consequences that deserve investigation.[13] This approach is also supported intuitively by policyholders. No-one is keen on paying for other people's imprudence. And those who behave particularly prudently would like their prudence to be acknowledged (here, we could also say "rewarded") by the insurance company in the form of suitable reductions in their premiums. Until the end of the twentieth century, however, the technology necessary for effectively measuring the degree of the individual's exposure to risk was still lacking. That is why, at the end of the 1990s, the economic theory of insurance still considered

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[12] We shall not go into the debate about "fairness" here, since it is extremely complex and varied and would call for a separate study. However, we will come back to the problem of discrimination in the final section of this article.

[13] There is actually nothing new about this idea from a legal standpoint. Early modern legal doctrine already hypothesised the contract of insurance as a very special form of aleatory contract in which the insurer accepts a financial risk (known as the *susceptio periculi)* in exchange for a premium. The premium guarantees that the pact is binding, but before accepting the obligation, the insurer obviously wants to know what risk they are running in reality. Jurists pointed out that the contract's equity depends on the relationship between price and risk, so that the premium should not vary *arithmetically,* but *geometrically,* in other words not in absolute terms, but in proportion to the risk to which the policyholder is actually exposed (Oñate 1654, Tract. 36, Disp. 131, Sect. II, n. 16: 677 f.).

irrelevant the question of whether the principle of subsidisation was generally fair, since the only way to make the insurance mechanism function on the *collective* plane was, as we have seen, to ensure the existence of an equivalence between the total amount of premiums received and the total losses expected by the insurance company (Farny 1995; Innami 1996). That the principle of equivalence led to a different conclusion on an *individual* plane obviously escaped nobody's notice, but since there was no way of directly measuring the risk transferred to the insurance company by each individual, the question was simply ignored (Farny 1995).

From the beginning of the new century, the use of telematics technologies (such as the installation of black boxes in vehicles), together with digital devices (such as mobile phones), has created unprecedented possibilities for monitoring individuals' driving behaviour and, as a consequence, modifying their insurance premiums to suit their real exposure to risk.[14] In our research, we investigate how this is done in practice and what opportunities and problems it generates in the relationship between insurance company and policyholder.

The introduction of behavioural variables into actuarial calculations

In order to understand how telemetry-based technologies impact on the valuation of policyholders, we interviewed insurance companies with extensive experience in this sector, because they were some of the first to sell third-party liability motor insurance based on the detection of drivers' behaviour. The telematics programs currently in use are typically formulated as pay-as-you-drive (PAYD) and pay-how-you-drive (PHYD) policies: in the first case, what is evaluated is the number of kilometres driven by policyholders over a certain period of time (e.g. a month), while in the second case it is their "driving style", for example whether they comply with speed limits, whether they drive by day or by night, whether they swerve or brake brusquely, whether they drive on city streets or country roads and so on. This information is fed back to the driver through an app on the policyholder's mobile phone. The telematics app conveys both granular and aggregated information. Every trip is detected and recorded, and criticalities (e.g.

[14] In the more innovative forms of mobile telematics, behavioural data are not produced by a black box installed in the vehicle (although this is still the practice among the Italian insurance companies that we interviewed), but by a mobile phone paired with a smart tag fixed to the vehicle's windscreen. While use of the mobile phone generates technical problems that do not apply in the case of the black box, the accuracy of the behavioural data it produces is now 90–95% compared to that of the behavioural data detected by a black box associated with the vehicle (Interview E.1, 30 March 2021). The behavioural variables detected are essentially the same in both cases.

excess of speeding, phone distraction, etc.) are visualised on the app after every trip. In addition, the policyholder receives an overall risk score which is usually updated monthly and measures the estimated dangerousness of the individual driving style. The telematics policies currently on offer on the Italian market combine both pay-as-you-drive and pay-how-you-drive features. In practice, this comprises the introduction of *behavioural variables* into actuarial calculations.

Professionals we interviewed confirmed that the first step they have to take to conduct this assessment is the creation of clusters of policyholders who are differentiated on the basis of classical actuarial variables: driver's gender and age, type of vehicle driven, driver's previous claim history (on which the established mechanism of the no-claims bonus is based) and place of residence. The historical data available enables a preliminary assessment to be made of the statistical probability that a given policyholder (e.g. a man aged 40 who lives in Milan, drives a Fiat Panda and has never had an accident) will file a claim in the following year. This operation is the crucial foundation for a first tarification of policyholders differentiated by segments according to standard actuarial methods.

The second step is to build on the traditional actuarial valuation by adding an assessment of risk exposure based on behavioural data. Our interviews reveal that behavioural data are essential for increasing the *variance* explained, i.e. for understanding why some of the individuals who belong to a group have a lower-than-average estimated probability, while others have a higher-than-average estimated probability. To go back to the example above: if the man aged 40 who lives in Milan, drives a Fiat Panda and has never had an accident has a 10% statistical probability of filing a claim in the year after he has bought the insurance policy, the behavioural valuation will help the company improve its estimate of probability associated with the single individuals belonging to the segment in question. In the opinion of one of our interviewees "one thing is certain: the delta risk factors[15] detected by the technology applied to insurance are objective and statistically measurable" (Interview C.2, 25 March 2021).

According to the metaphor used by another interviewee, we need to

> imagine this kind of exercise as something like a Rubrik's cube: on the first part of the face is the human world … I go to take a look at how [the policyholder] behaved last year from the point of view of my portfolio, from the point of view of my customer basket, so as to use probability to calculate how things will look next year. What we have here, then, is *a concept of pure*

[15] Delta risk factors are variables (in the case of motor insurance, e.g., harsh braking and sudden tailgating) which can affect the average risk exposure of individuals belonging to a certain pool. Aggressive driving style, for example, can cause a deviation from the average, making a difference in risk assessment that has high information value for the insurance company.

> *statistics*. On top, [you always have to] imagine then how the cube will look on the next side … [Here] I look at all the *parameters of the telematic data* and, as a consequence, all those data that I cannot see,[16] which are not the same as those I can download from an estimate, or that I can download from a databank that may be provided by the Ministry of Transport, or by the National Institute of Statistics (ISTAT), or again by the vehicle drivers' portal, so everything that I cannot see – and that's the boost that I get from telematics – that is to say that it manages to give me real data … The last side of the cube is everything that we end up creating with the *models of artificial intelligence*. (Interview F.1, 9 April 2021)[17]

This last phase is crucial. As we have seen, the company has a vital interest in guaranteeing that the total sum of the pure premiums received in advance is equivalent to the total sum of the compensation that the company will then have to pay out during the period stipulated as the policy's duration. This means that the claim is more relevant than the crash: that is because drivers do not file a claim for every crash, or because the severity of the crash is underneath their deductible/excess, or because drivers want to avoid being penalised by losing or worsening their no-claims bonus when the time comes to renew the policy.

So when a company has access to behavioural data, it starts from the filing of a claim in which its customer is at fault. This is the point at which data scientists step in. One of them explained to us that

> we take information from our own data to determine when a crash occurred to then get a view of what behaviour occurred immediately prior to a crash … It enables us to build *a view of risk* in a way that is *directly correlated back to those drivers' actual behaviours*. (Interview E.1, 30 March 2021)

The result is a predictive model: by monitoring driver behaviour for 91 days, the algorithmic data processing can "predict with a high degree of certainty what behaviours are likely to lead to a crash in the next 90 days" (Interview E.1, 30 March 2021). This predictive model refers to the actual driving behaviour and not only, as traditional actuarial models, to the claims that have been filed. One of the interviewees

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[16] He cannot see the data referred to single individuals because the statistics "obliterate the individual" (Daston 1983: 23) and instead offer up "averages" derived from the aggregation of many sets of individual data.

[17] The meaning of Rubrik's cube metaphor is, in our opinion, that the addition of behavioural data to usual statistical variables should not be understood as a mere additive process. Like the real world, Rubrik's cube is a three-dimensional reality whose faces can be continuously recombined to obtain information that would not be available if the observer merely looked at one face of the cube at a time under predetermined conditions.

explained this difference by stating the need to distinguish between an "actuarial score" and a "behavioural score".

> An actuarial score predicts claim frequency, but a behavioural score is … basically looking at those risk behaviours that … contribute towards loss, but are not tied back to the insurance process. (Interview E.1, 30 March 2021)

The first element, the actuarial score, is the one traditionally used by insurance companies for the purpose of guaranteeing the profitability of their business. The second element, the behavioural score, measures an additional risk factor known as "driver aggressiveness", so the prudence or the lack of prudence practised when driving. This score is an aggregated result of telematics data processing and is usually layered into three profiles: low risk exposure (advanced driver), moderate risk exposure (normal driver), high risk exposure (reckless driver). An interviewee pointed out that, even if "there's a very big overlap between the two elements, because the elements that lead to safety and elements that create claims are … incredibly highly correlated" (Interview E.1, 30 March 2021), the actuarial score and the behavioural score are not identical and the difference is conceptually very important.

For insurance companies, the behavioural score provides a more accurate forecast of which customers are more likely to get into a crash irrespective of whether they will file a claim. The argument goes: if you can reward or penalise members of the same segment more selectively based on their actual behaviour, you can retain the better customers, while reducing the risk of churning and improving the loss ratio. This means that insurance companies can adopt commercial policies whose ultimate purpose is to practise "cream-skimming" (Cather 2018). From the insurance companies' standpoint, telematics thus constitutes an unprecedented opportunity for managing the classical problem of adverse selection. For one of our interviewees "the great advantage of behavioural tarification is that it provides an objective, rational and structural way to industrialise discounts that maximise customer retention" (Interview C.2, 25 March 2021). And for another interviewee "that is the real keystone to the entire system" (Interview F.1, 9 April 2021).

On the one hand, then, Barry and Charpentier are right: the aim of using digital technologies in third-party liability motor insurance is to "*refine* the existing segmentation thanks to new parameters" (Barry and Charpentier 2020: 8 emphasis in original).[18] Seen from another

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[18] And without going to the extreme case of the "pool of one", which is often discussed in the literature with a degree of concern (Ramasastry 2012; Harrington 2017; McFall et al. 2020).

perspective, however, the detection of behavioural variables leads to a truly innovative evolution in the form of forecasting used by insurance companies. Digital valuation searches out "behavioural patterns" that enable it to explain why certain individuals within the average of a given segment can be said to perform better, while others perform worse. The aim of behavioural valuation is thus to help the insurance company identify those individuals within the given segment who for behavioural reasons are more likely to file a claim. One of our interviewees points out that "what we're trying to do in our industry … is identify those behaviours that are *causative* of risk, that are *controllabl*e … and are *predictive*" (Interview E.1, 30 March 2021).

The company rewards or penalises specific behaviours, adapting the tariff or discount when the policy is renewed. This paves the way for us to return to a point we mentioned in the introduction: the customisation of the premium. If by customisation we mean a tarification based entirely on each individual's personal data, then we can certainly say that digital insurance premiums are not customised. As we have seen, the basis for tarification still remains the classical actuarial model, based on variables *independent* of individual behaviour, such as age and gender.

If, on the other hand, we take customisation to mean an adaptation of the premium to take into account the individual's actual risk exposure, we can say that insurance companies have started experimenting with "tailor-made" premiums, based on monitoring the policyholders' behaviour. People belonging to the same segment may pay less or more (because they do or do not get a discount) according to their actual score. People belonging to the *same* segment, in other words, can pay *different* premiums.

Confirmation of this comes from the Italian insurance professionals we interviewed, who told us that companies are moving over from a logic of "discount upon renewal" (a simple commercial leverage that is applied to everyone when the telematics policy is renewed) to a more complex logic of "price upon renewal", in which behavioural data are "built into the actuarial architecture" (Interview C.2, 25 March 2021) to customise the premium according to specific predictions for single individuals.

The impact of telematics on communication with policyholders

Shifting our focus from insurance companies to individuals, we next asked insurance professionals how they perceive the response of policyholders to the change in method used to assess their exposure to risk, and what consequences they expect this change could have on the relationship between policyholders and insurance companies.

The interviews we conducted with Italian insurance companies illustrate a situation that is significantly different from the one that is normally portrayed, with a degree of concern being expressed in the literature, above all with regard to the issue of privacy. One company that decided to do away with telematics policies told us that the people who bought their telematics policies failed to download the app that was supposed to collect the data and then transmit them to the company (Interview D.1, 03 November 2020). The same problem was illustrated very clearly by another company that has been using telematics motor insurance policies since the beginning of the century. Speaking about the situation in Italy, one interviewee explained that those who paid for a telematics insurance policy did it "essentially because of the discount, rather than … for the opportunity to understand their [driving] behaviour" (Interview B.1, 24 March 2021). That is because Italian law obliges insurance companies that collect telematics data in their third-party liability motor insurance to give policyholders an entry discount, which is sometimes termed "welcome bonus", or "flat discount". When the policy is renewed in due course, a further assessment based on kilometres driven and customer's driving style is then taken into consideration to decide a possible future discount.

The same person (Interview B.1, 24 March 2021) told us that the flat discount can account for as much as 25% off the standard tariff, constituting a strong incentive for drivers who want to save on their car insurance. This is also confirmed by the fact that a preference for telematics policies was first encountered above all in those regions of Italy (in the centre and south of the country) where tariffs are higher because of the greater frequency of accidents. Telematics car insurance policies are thus said to have achieved a greater penetration in central and southern Italy for the perfectly predictable reason that, in those places where the premiums are higher, people have a greater incentive to save money. Yet, this also means that concern about the use of data is given less importance and remains marginal when compared to the economic advantage that can be achieved from a discount on the insurance premium. Our interviewee believes that the behavioural analysis

> was evidently not highlighted very much at the moment when the policy was sold, so we had a degree of … I don't want to say conflict, but anyway some resistance to understanding and managing the product when the time came for renewal, maybe because the customers who had bought the policy had done so essentially for the discount rather than for, shall we say, the possibility to get to know their own behaviour. When they found maybe that, on renewal, their discount was not so generous as the one they had enjoyed in the previous year, because they had driven more, or because they had been driving in ways that were not exactly safe, this generated a basic need for management also in the point of sale. (Interview B.1, 24 March 2021)

The message conveyed in this and other interviews seems to be that, when the first third-party liability motor insurance policies based on a behavioural valuation of the driver were introduced in Italy, there was none of what could be described as “policyholder education in telematics”.

Another interviewee explained to us, in a very disenchanted tone, that when the insurance company first launched telematics third-party liability motor insurance policies at the beginning of the century, companies still had the habit of sending text messages to their customers’ mobile telephones to update them about the status of their tariff. This practice was sometimes perceived as a form of intrusion and generated concerns about privacy. In 2021, on the other hand,

> to talk about problems of privacy because your car knows where you are is a bit silly, because these days everything, starting with your smartphone and continuing with your TV and your smart speakers … that is to say, everything knows where you are and what are doing, doesn’t it? So for me that has now become an issue … *that’s a false problem, it’s more of a leftover from the past.* (Interview C.2, 25 March 2021)

That obviously does not mean that privacy is not a significant issue, both legally and ethically. But insurance executives perceive it as a false problem in practical terms because habituation to digital technologies gives the impression that privacy is downright impossible.

One unprecedented possibility that the digital valuation of the policyholder’s driving behaviour offers today, on the other hand, is that of establishing a circular communication relationship between the insurance company and its customers. In this case, the combination of telematics technology with the mobile phone turns out to be crucial. The traditional insurance company would focus most of its dialogue with its customers on the phase leading up to the signature of the policy, employing questionnaires to gather information that it would then use to place the customer in a given actuarial class. Further communication was triggered later only by claims or at the renewal of the policy (which also included the risk of losing the costumer). In the more evolved version of motor telematics, on the other hand, policyholders receive targeted information about each single trip on an app, together with tips about any critical issues (e.g. when and where the customer broke the speed limit, swerved sharply or made a forbidden U-turn). At the same time, policyholders can call up their total score and the discount from which they can benefit if and when the time comes to renew their policies.

According to our interviewees, this technical possibility of feeding information back to the driver enables policyholders to know in real time how their driving style is evaluated by the insurance company. A computer scientist told us

> that's where we find the mobile program to be so unique … *mobile provides that feedback loop to drivers*, that's unique to that element and is temporal, and then you can layer in incentives like reward programmes, like changing premiums every 6 months or every 12 months, and you can show visually how individual driving behaviour leads to that. (Interview E.1, 30 March 2021)

From the insurance companies' and software providers' viewpoint, the purpose is to improve not only drivers actuarial scores, but also their behavioural scores – a significant step towards the ideal that underlies all road safety programmes, i.e. zero road accidents.

We wondered to what extent these ideals correspond to reality. The insurance companies we interviewed told us that historical data collected in the most recent telematics programs, ones that have only been active for a few years, do not yet enable statistically relevant conclusions to be drawn. One software provider realised that

> there is the Hawthorne effect that says that, you know, someone can change their behaviour for a certain given period of time while being monitored, but that Hawthorne effect fades over time. (Interview E.1, 30 March 2021)

Nevertheless, one insurance company detected a slight drop in the frequency of incidents, although not of their severity (Interview B.1, 24 March 2021). For that company, it was still early to say whether the telematics group can be distinguished in any statistically significant way from the non-telematics group. Another company, which classifies driving behaviour in three different buckets – more "evolved" drivers, "intermediate" drivers and "reckless" drivers – noticed a decrease in the level of risk. In the short and medium terms

> if we assign a value of 100 to the people who are in one segment rather than another, the great majority of customers in the higher-risk or medium-risk segments decrease towards medium-risk and low-risk classes. (Interview C.2, 25 March 2021)

This effect can be measured statistically, although it is hard to understand to what extent it is due to the data fed back to drivers. The interviewee himself actually pointed out that it is impossible to say with certainty

> whether the effect is related to education, to being afraid of paying more for the policy or to the fact that customers are annoyed when they find

> themselves assigned to the bad class; it is probably a combination of all these things. But the effect is visible. (Interview C.2, 25 March 2021)

In the opinion of many of our interviewees, in any case, "incentives are incredibly important" (Interview E.1, 30 March 2021).

> Just knowing how you drive, without maybe receiving some little gadget as a reward for virtuous behaviour, turns out to be, shall we say, a strategy that is rather incomplete and limping. (Interview B.1, 24 March 2021)

Many telematics programs that have been adopted in countries outside Italy do in fact make allowances not only for discounts weighted by parameters, but also for a series of incentives that range from little gadgets to cashback when filling the tank, vouchers for buying trips and so on. These incentives have been found – with some caution – to be of fundamental importance for reducing the incidence of road fatalities (Stevenson et al. 2018; Peer et al. 2020; Stevenson et al. 2021).

In any case, one significant element of this new relationship of communication between the insurance company and policyholders is that the insurance company can, for the first time, embark on "educational" or "coaching" actions that tend towards being *proactive:* instead of waiting for accidents to happen, as is traditionally the case, the insurance company adopts strategies that are designed to call attention to risks and as far as possible mitigate policyholders' exposure to danger. This would mean a profound transformation in the insurance company's mission and business model.

This already happens in mobile telematics, because drivers are well aware that allowing themselves to be distracted by their mobile telephones will be monitored by the app, something that does not happen with the black box. As being distracted by the telephone is the third cause of road accidents, dissuading the use of mobile telephones while driving is already a way of being proactive. But the intention is to intensify operations of this kind enormously in years to come. One of our interviewees told us that he and his team

> are grading drivers on their safety and providing information back to them. And our goal is that they *internalise that information* and become safer themselves; (Interview E.1, 30 March 2021)

while another interviewee stated: "This is our plan for 2021 in terms of products: *coaching*" (Interview H.1, 31 March 2021).

Discrimination and fairness in behavioural valuation

This last section of our article deals with a question of fundamental significance for the sociological analysis of insurance and for our investigation of the innovative potential of recent digital technologies: the impact that the valuation of customers with a telematics motor insurance policy could have on the risk of discrimination and on the fairness of the insurance mechanism in general. What emerges from the interviews we have conducted so far is that insurance companies are aware of the fact that the use of behavioural data to evaluate their customers can raise unprecedented questions about the social impact of their procedures. One of our interviewees told us about his uncertainty whether "it is not so much the insurance companies that are not ready, but more the consumer who is not ready" (Interview D.1, 3 November 2020).

Under the heading of "discrimination", the problem of the propriety of procedures of algorithmic evaluation is often tackled as part of the complex, sophisticated ethical and legal debate about algorithmic fairness, the idea of equality in insurance practices and corresponding expectations of algorithmic accountability. Twenty years ago Tom Baker (2003: 275) had already argued that "any particular individual is only one technological innovation away from losing his or her privileged status" of low-risk case, and that in principle new risk classification systems could penalise people previously ranked as "good customers".[19] Moreover, many are of the opinion that achieving a balance between fairness, equity and non-discriminatory practices in the insurance industry is an extremely hard challenge to meet. The problem is technical–actuarial, legal, ethical and political, all at the same time (Lehtonen and Liukko 2015). It is even impossible to provide an unequivocal answer to the question "How fair is actuarial fairness?", since equity does not always imply the absence of discrimination, nor can it be said that everything that is non-discriminatory is necessarily fair. The notion of fairness is complex and multidimensional (Minty 2021). Rather than providing more input to this debate, our intention here is to focus on a more circumscribed question: is the use of behavioural data discriminatory – or discriminatory in a way that is different from traditional insurance practices?

We start from a specific case. In 2004, the European Union issued a Directive, better known as the "Gender Directive" (2004/113/EC), to govern the terrain of unisex tariffs. The directive prohibited the use of gender to differentiate insurance tariffs, considering reference to the difference between males and females to be a discriminatory practice (Art. 5). Nevertheless, the directive contained a get-out clause that

[19] Baker referred to genetic testing in health and life insurance.

legitimised the use of gender difference when insurance companies could demonstrate that it was correlated statistically to the company's expected losses on the basis of a probabilistic assessment conducted on claims filed in the past. This exception was then challenged by the Belgian consumers' association Test-Achats. In 2011, the European Court of Justice accepted the challenge, prohibiting the use of gender difference in insurance tarification once and for all (C-236/09, Test-Achats).

The paradoxical result of this ruling has been that of indirectly creating new unfairness and discrimination. The Court of Justice referred to the general criterion (built on the Aristotelian idea of justice) whereby similar cases should be treated in like manner and different cases in a different manner, which is the basis of the risk transfer principle. In the case of third-party liability motor insurance, it has been known for some time that females are less exposed to risk of accident than males, but for the Court of Justice this depends not so much on gender in itself as on other variables, such as employment (men use their cars more for work), or excessive alcohol consumption (men drink more than women), although these are factors that are hard for insurance companies to monitor. The European Court of Justice thus seems to be saying that gender is being used as a proxy for other variables that are causally correlated to the different accident rates of males and females and, as such, is to be considered discriminatory (Cather 2020). In its judgement, the Court of Justice tried to find a tricky balance between ethical commitment (a certain idea of justice), technical problems (actuarial calculations) and legal prerequisites (nobody can be blamed for qualities not directly connected with the subject of blame).

But the introduction of unisex tariffs has obliged companies to reduce the premiums paid by men and increase those paid by women, despite the fact that men constitute more risk for insurance companies than women. In fact, if they are to comply with the principle of equivalence, insurance companies must guarantee that the pure premiums they receive are sufficient to cover expected losses. Unisex tarification eliminates one important factor of segmentation, obliging companies to opt for homogeneity when spreading expected financial risks. Let's suppose, for example, that the expected losses remain unchanged (let's say €160): while women previously paid a pure premium of €60 and men a pure premium of €100, with a unisex tariff both will pay a pure premium of €80. As a result, women end up having to *subsidise* the costs caused by men to insurance companies. If we then also consider that women on average earn less than men, the increase in the price of third-party liability motor insurance policies for women and the corresponding decrease in the price of third-party liability motor insurance policies for men have been considered by many observers to be an involuntarily iniquitous and discriminatory measure (Porrini 2011; Cipriani 2013; Fusco and Porrini 2020). Ultimately, then, it is paradoxical that unisex rating produces differences in insurance premiums for females and males, because when conditions remain unchanged, although they pay the same premium, women pay more than men for the risk the former really transfer to insurance companies (Fusco and Porrini 2020: 9).

There are at least two crucial points at stake in this exemplary matter. The first concerns the principle implicit in the ruling of the Court of Justice, which accepted the challenge lodged by the association Test-Achats, i.e. the fact that it is unfair to use proxy data even when they have a strong statistical correlation with the company's expected losses and thus comply with the principle of actuarial fairness.[20] The second point is that the entire issue that led up to unisex tariffs turns on a non-behavioural variable. But what changes if the company can have access to the values of behavioural variables? In other words, what changes if the company can observe how its policyholders really behave in practice?

One of our interviewees introduced an extremely interesting (and debatable) line of thinking about this, one that we believe deserves to be quoted here at length. In his opinion, an analysis based on the behavioural variables that telematics are capable of monitoring

> is *a very different analysis from any other way that insurance is used,* right? The rest of insurance is looking at *proxy variables* … that are *correlated* but not *causative*. What we're trying to do, specifically, is *identify those behaviours that are causative of risk* … These have turned out to be a really important element and *non-discriminatory*, because all those other elements, I mean … you yourself could move to the south of Italy and be paying more for insurance all of a sudden, but you're not a different driver, it just happens to be where you move to, your postcode changes, and the case of someone in the States is that if they get married or they get divorced or something happens to their credit, then all of a sudden they're paying more for insurance as a result of that, and none of that increases their risk, *it just happens to be the way that actuarial analysis looks at it,* looks at large groups of people and then tries to find patterns in laws.
> We're looking at *behavioural elements* and we're servicing that back to the driver. It's a very different approach from looking at risk. *I don't think there's a worry about penalising drivers in this case,* because we know that the drivers that have very high risk points are also drivers that get into

[20] Much of the discussion about algorithmic fairness concerns the difficult trade-off that ought to be achieved between predictive accuracy (as we know, proxy data often offer very strong correlations, which makes them useful for various different forms of business) and indirect discrimination. Cf. Loi and Christen (2021) for an overview of the debate from an ethical rather than legal standpoint.

> crashes and are also drivers that make claims. (Interview E.1, 30 March 2021)

In formal terms, this line of thinking corresponds exactly to the approach adopted by the European Court of Justice and described above, which considers the use of proxy data to be unfair. In traditional procedures used by insurance companies, individuals are not evaluated on the basis of their specific conditions and real behaviour, but because they are labelled as belonging to a group, such as that of individuals of female gender, or of divorcees, or of drivers who are resident in southern Italy. This kind of valuation is based on correlation, which notoriously does not necessarily correspond to any causal relationship. On the other hand, a valuation based on behavioural variables would not be unfair, so would also not be discriminatory, because it would be based neither on proxies, nor on statistical generalisations which, however well they may be segmented, place individuals in a group without taking their specific exposure to risk into account. The valuation made possible by telematics tools targets persons as individuals, taking their behaviour into account, without reference to any given groups, and so – we would add – without reference to any form of solidarity. Nobody would find themselves having to subsidise costs caused by others.

This substantial erosion of the principle of subsidiarity has stirred up a hornet's nest among analysts, as the customisation of premiums would lead to a drastic transformation of the principle of mutuality that has traditionally underpinned insurance. One unintentional effect of the predictive valuation of policyholders' behaviour would be the fact that the better we can predict future risk, "the less we'll be willing to share our fates with others" (Croll 2012). So the inevitable result would be the end of subsidisation.

Nevertheless, insurance practices that use behavioural data paint a different picture. To our way of thinking, the first thing is to draw a distinction between the principle of subsidisation and that of risk spreading. As we have seen, subsidisation is the issue at stake when members of one segment offset members of a different segment (younger drivers offset older drivers, women offset men and so on). The issue is more strictly one of risk spreading, on the other hand, when members of one and the same pool contribute to reimbursing the total losses expected within that pool. Segmentation operates in the opposite way to subsidisation, but does not do so without the classical mechanism of risk spreading, which remains the underlying foundation that makes the insurance industry function.

The behavioural valuation of policyholders for third-party liability motor insurance does not stop members of a pool from sharing a destiny that is still, to a considerable extent, predicted by non-behavioural factors. As we have seen, behavioural data are only complemented at a later stage in the actuarial architecture whose purpose is to identify the policyholders with whom a specific loss prediction is associated. This means that behavioural data drive the principle of risk transfer to extremes: those who have a better risk profile – either because they drive less, or because they drive more prudently – contribute less to reimbursing the expected losses within the pool than those who have a worse profile. Taken as a whole, though, the mechanism is still based essentially on risk spreading.

Behavioural data could nevertheless intensify the *tension* between the individual and the group. To our way of thinking, a real sea-change would only come about if the destiny (so the pure premium) were calculated *exclusively* on the basis of behavioural data. If that were the case, there would no longer be any pools, but in fact only "behavioural tribes", in which, as Cathy O'Neil puts it (2016, ch. 9) "those who act alike take on similar levels of risk". The underlying principle of risk pooling and spreading would then have to be fundamentally redesigned.

Conclusion

In concluding our exploration, we want to mention some considerations about possible social consequences of the use of digital technologies and algorithmic prediction in the field of insurance. Since Ewald (1986), research has shown that the impact of insurance on society depends on the form of solidarity in the management of future risk, which is closely related to available techniques to calculate and control them. Until now, these techniques were based fundamentally on statistical actuarial models. If we now look at the introduction of algorithmic techniques that follow a different logic, how does this affect the distribution of responsibility and risk management in society as a whole?

Our analysis shows that, at the moment, real innovation lies in the possibility of focusing on individual behaviour in a way that was previously unfeasible, which affects the relationship between insurance companies and policyholders and thereby also the respective business model. But what consequences does this have for the form of social solidarity and the willingness to take risks?

While it is true that risk often depends on individual behaviour, it is also true that behaviour does not always depend on the individual. Any connection between injury and behaviour raises tricky questions about the idea of responsibility and the criteria according to which a person should or should not be blamed for that injury. As Tom Baker (2003) points out with respect to moral justifications of risk classification, if someone deserves low-risk status, the moral claim to benefiting from that status is a strong one. For the same reason, if high-risk status is not deserved (as in the case of battered women), the moral claim to penalising it is weaker. Yet, the issue is that it is not always clear, as Lehtonen and Liukko (2015: 164) argue, "to what extent a person can be held responsible for his or her lifestyle, social [and cultural] milieu, or area of residence".

On the other hand, if risk is attributed to the individual, it does not necessarily follow that policyholders want to accept responsibility for all their behaviours and for possible consequences. Insurance valuations should take this eventuality into account. Valuations that refer to behavioural variables ought presumably to continue being combined with actuarial statistical considerations to keep the basic mechanism of insurance working, but maybe a case can be made for increasing customisation by exercising greater freedom in defining groups and how they are made up – including the group of those who do not want to accept the burden of being evaluated on the basis of their behaviour. This leads to our second consideration.

Historically speaking, insurance was introduced not to induce individuals to keep their exposure to risks under control, but to relieve individuals of their worries about possible future damages. As François Ewald has pointed out (1991), insurance was introduced as a "liberator of action", to enable individuals to undertake risky businesses in a relatively protected manner. The contingent financial certainty offered by insurance coverage allows policyholders to venture into activities whose future course, despite all the risks to which the enterprise exposes the insured, can be considered a "rival choosable" to the future course that would be realised if the insured were to give up the enterprise (Cevolini 2019b). The traditional purpose of insurance, therefore, has never been that of reducing risks, but it could be said to have been more that of multiplying them, guaranteeing the possibility of managing their consequences (Luhmann 1996). For policyholders, the possibility of falling ill, of having a car accident or that their house burns down is not reduced: if anything, it increases, as illustrated by the chronic problem of moral hazard (Stone 2002).

Moral hazard is, notoriously, a crucial issue of actuarial science (Baker 1996). The idea is that if I know that my insurance company will compensate against damage, I have less incentive to be careful and prevent an accident from happening.[21] The result can be an increase in risk exposure and consequently in prospective claims (Arrow 1971; Stiglitz 1983; Heimer 1985.). The paradox is, in the end, that "less loss

[21] In this respect, Heimer (1985) speaks of "reactive risks". Ferdinand Tönnies (1917) had already pointed out that this happens because the financial certainty provided by coverage makes the policyholder somehow unconcerned about the damage. On Tönnies's sociological investigation about insurance see Cevolini (2019a).

[for the insured] from a loss means more loss [for the insurer]" (Baker 1996: 270).[22]

Since the early 2000s, insurance companies have begun to address the problem of moral hazard emphatically in terms of prevention (Baker and Simon 2002a; Ericson et al. 2003). Scholars suggested that this trend was an effort to make people "more individually accountable for risk", that is, to let policyholders (at least in part) "embrace the risks" they wanted to insure against (Baker and Simon 2002b: 1).[23] From the insurance companies' standpoint, the question was how to "govern the insured", moving from the assumption that a safer environment not only means a better loss ratio for insurers but also materialises in lower premiums for insureds (Ericson et al. 2003). The intent was to explicitly turn insurance companies into "loss prevention companies" and thus to "stop claims before they happen" (Ericson et al. 2003: 271). However, how to reach this kind of self-education of policyholders was not clear and at the end insurance companies resorted to usual (and more practical) solutions such as spreading risks.

It now seems that the problem of moral hazard can be to some extent "technically controlled" by means of telematics technology (Van Hoyweghen et al. 2006: 1231). If 20 years ago the basic idea was to make drivers accountable for "being aware of crash risks and the consequences of miscalculating them" (Ericson et al. 2003: 272), yet without knowing how to detect such awareness, the feeling now is that by means of telematics data it is possible to *calculate* precisely *this miscalculation*. However, telemetry-based technology does not *control* the policyholders' behaviour. Their driving behaviour, instead, produces telematics data which is algorithmically processed to extract information. The latter is not only used by insurance companies to implement a more individualised risk assessment, but it is also fed back to drivers in order to give them the opportunity to control themselves. When this *self-control* is carried to the extreme, it can turn into a particular kind of inhibition. We wonder, then, if the introduction of behavioural valuations that burden the present with responsibility for the future could be, for policyholders, a source of anxiety that would eventually transform insurance into an "inhibitor of action" (Cevolini and Esposito 2020). Research will have to clarify

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[22] Insurance companies have attempted to curb moral hazard by including clauses in policies whose purpose is to again increase the policyholder's incentive to be prudent. Loss-prevention measures such as rewards (e.g., no-claims bonus) and penalizing agreements (e.g., franchise and deductible) actually serve to encourage policyholders to keep their exposure to dangers under control and to assume at least some of the responsibility in case an accident occurs (Heimer 1985).

[23] Twenty years ago Baker and Simon (2002b: 3 ff.) spoke of a shift "from spreading risk to embracing risk", although they admitted that the latter does not remove the former.

whether, and to what extent, this may affect the social function of insurance and individuals' ability to enact the future, starting from available insurance coverages.

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