On the Consequences of Behavioral Adaptations in the Cost-Benefit Analysis of Road Safety Measures

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Abstract

It is sometimes argued that road safety measures or automobile safety standards fail to save lives because safer highways or safer cars induce more dangerous driving. A similar but less extreme view is that ignoring the behavioral adaptation of drivers would bias the cost-benefit analysis of a traffic safety measure. This paper derives cost-benefit rules for automobile safety regulation when drivers may adapt their risk taking behavior in response to changes in the quality of the road network. The focus is on the financial externalities induced by accidents because of the insurance system as well as on the consequences of drivers' risk aversion. We establish that road safety measures are pareto-improving if their monetary cost is lower than the difference between their (adjusted for risk aversion) direct welfare gain with unchanged behavior and the induced variation in insured losses due to drivers' behavioral adaptation. We also show that our results are robust to the endogeneous determination of automobile insurance policies in an optimal contracting setting with moral hazard.

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1 Introduction

Behavioral adaptations of drivers to safety measures is a well documented phenomenon; see OECD (1990). Following changes in the road-vehicle system affecting either highways safety or vehicle safety, road users sometimes adapt their behavior in a manner inconsistent with the initial goals of the safety measures: indeed, safer highways and safer cars often induce more dangerous driving[1]. Because of this behavioral adaptation, the decrease in accidents and fatalities may be lower than what was initially expected, and it may even fully vanish. In particular, using US data (1947-1972), Peltzman (1975) claimed that such offsetting effects have been virtually complete and that regulation has not decreased highway deaths. However, most studies lead to less clear-cut conclusions and they most frequently show that behavioral adaptation only mitigates the initial impact of road safety measures and that these measures still entail some residual effects[2].

Behavioral adaptation to safety measures has been widely analyzed with the analytical tools of social psychology and cognition theory. In particular, Wilde (1982, 2001) develops a theory of ***risk homeostasis*** according to which individuals are prepared to accept a given target level of risk and he derives a number of implications for safety and health. In Wilde's theory, the dynamics of individual behavior results from a gap between the perceived level of risk and an (exogenously given) target level of risk. This gap follows from the fact that individuals have bounded perceptual skills. However, if the risk-taking behavior by drivers is put within the framework of expected utility maximization (for instance by speed choice), then risk homeostasis is possible only under very restrictive conditions -see Janssen and Tenking (1988). Nevertheless, behavioral adaptations to changes in the road transport system is a much more general phenomenon than risk homeostasis which is expected to hold under fairly general conditions. The fact that compensation is partial or total (or even that there is overcompensation) is a matter that can be settled on the basis of empirical observations only. As summarized in the key conclusions of an OECD (1990) expert group report "Behavioral adaptation

[1]See for instance the analysis of Peterson, Hoffer and Millner (1995) on the behavior of drivers of air-bag-equipped cars. They conclude that "air-bag-equipped cars tend to be driven more aggressively than cars without air-bags and that the additional aggressiveness appears to offset the effect of the air-bag for the driver and increases the risk of death to others".

[2]Graham and Garber (1984) critique the functional form of Peltzman's model and, saying the opposite of what Peltzman says, they argue that "safety standards have saved tens of thousands of lives during the 1970s". Later on, works by Chirinko and Harper (1993) and Keeler (1994) have reinforced the empirical plausibility of the "offsetting behavior hypothesis".

(to changes in the road transport system) exists, and does have an effect on the safety benefits achieved through road safety programs. Results indicate that, generally, behavioral adaptation does not eliminate the safety gains obtained, but it does reduce the effectiveness of road safety programs in a number of cases".

Given the empirical fact that drivers adapt their behavior to changes in their environment (particularly to road safety measures), an open question is how these behavioral adaptations should be taken into account in the cost-benefit analysis of public investments and traffic regulation. In particular, behavioral adaptation may totally or partially offset the safety gains of an investment transport program. These adaptations may correspond to a welfare gain to individuals, for instance when individuals enjoy a more pleasant driving or chose a higher mileage, even if these side effects were not the main goal of the program. So, one may actually wonder whether and how to include these adaptations in the balance of costs and benefits of road safety programs.

The following analysis will bring insurance-linked externalities into prominence. Indeed, we must keep in mind that drivers are (at least partially) insured against the losses they may cause when they are responsible for an accident. Reckless drivers not only take a risk for themselves but, when they bring about an accident, they are also the source of an externality to the detriment of all other drivers because of the insurance system. One may even say that the essence of insurance contracting under moral hazard is to trade off the incentives for drivers to be more cautious in order to reduce this detrimental external effect with the positive effect of a better risk sharing between drivers. From our analysis, it emerges that the insurance mechanism is the fundamental reason why behavioral adaptations should be taken into account by the social planner: the social cost of these adaptations is nothing but the additional burden imposed on the drivers as a whole by this insurance-linked externality.

Blomquist (1988, pp 32-39) emphasizes the fact that individual demand for traffic safety tends to be too low because of such insurance external effects, which include "the potential shift of some medical costs to those not involved in an accident,..., the lack of precise experience rating for automobile insurance and possibly incomplete compensation for damaged parties through the courts especially when time costs and death are involved". He also draws attention to the fact that conventional cost-benefit analysis assumes that drivers are passive toward road safety measure (for instance mandatory safety standards) and that they do not change their safety-related behavior. He concludes that the assumption of driver's passivity biases the conventional cost-benefit studies toward positive net benefits of an active traffic safety policy. In what follows, we will show that both issues (insurance external effects and behavioral adaptation) are in fact tightly connected: forgetting the behavioral adaptations biases the cost-benefit analysis in so far as the risk-taking behaviors by some drivers make the other drivers incur additional insurance costs.

In order to develop such an analysis, we will insert risk-taking behavior by drivers within a simple one-good model of optimal resource allocation under uncertainty with endogenously determined insurance contracts. This setting will allow us to identify the way in which the conventional cost-benefit rules should be rectified because of drivers' behavioral adaptation. It will also highlight the effect of drivers' risk aversion on the willingness to pay for a traffic safety measure.

From now on, two shortcomings of the present paper should be acknowledged. First, for the sake of clarity, we will only focus attention on the effect of road safety measures on drivers' risk taking behavior. However, a road safety policy may also induce an increase in the density of traffic and, in consequence, to additional congestion costs or to an increase in average accident risk[3]. In practice, a thorough cost-benefit analysis should not overlook these externalities which take place through the effect of road safety measures on traffic density. Secondly, we will only consider network related public expenditures, be they preventive (e.g. lane widening, line marking, lighting of freeways, ...) or protective (e.g. crash barriers). Vehicle safety will not be approached although it is an essential part of many road safety policies. Our results can easily be extended to the analysis of vehicle-related mandatory restraints (e.g. more restrictive crash tests or more efficient antilocking systems) when drivers may adapt their risk-taking behavior in reaction to changes in regulation[4].

The paper is organized as follows. Section 2 presents the basic model of drivers' behavior with accident risk. Section 3 develops the costs-benefits analysis of road safety programs when drivers change their safety-related behavior in reaction to changes in public investments. For simplicity, in this section, the insurance indemnity schedules are supposed to be exogenously given. In Section 4, we extend our results to the case where the insurance contracts are chosen optimally in reaction to changes in the parameters of the transportation system. Section 5 concludes.

[3] On the fact that the density of traffic affects average accident risk, see for instance Jansson (1994) and Small and Gomez-Ibanez (1999).

[4] Such an extension can be obtained from the authors on request.

2 A microeconomic model of accident risk

In this section, we analyze a simple model of road users' behavior. Assume that there are n drivers, indexed by $i = 1, \dots, n$. A typical driver is treated as an expected utility maximizer. The utility of driver i is supposed to be separable between final wealth w_i^f and effort e_i and it is written as $u_i(w_i^f) - e_i$, with $u_i' > 0$ and $u_i'' \leq 0$. Hence drivers are risk averse or risk neutral with respect to wealth and they dislike effort. A larger level of effort corresponds to a more cautious driving behavior which decreases the probability of accident. Let p_i denote the probability of an accident caused by driver i. It depends on drivers i's effort e_i and also on a parameter x that describes the safety of the road network. Hence, we will write

$$p_i = p_i(e_i; x)$$

with $\partial p/\partial e_i < 0$, $\partial^2 p/\partial e_i^2 > 0$ and $\partial p/\partial x < 0$: Changes in x reflect the modifications in the highways insofar as they affect the probability of accident, for a given behavior of the driver. For notational simplicity, we assume that all drivers are affected by the same road transport system parameter x and that the relation between the probability of an accident and the effort level is the same for all drivers.

Let $\tilde{y}_i$ be the damages (in monetary terms) caused by driver i in the event of an accident: $\tilde{y}_i$ is a random variable that corresponds to the total cost of an accident, including damages inflicted on other road users or other agents. For simplicity, we assume that the probability distribution of $\tilde{y}_i$ does not depend on e_i. In other words, the probability of an accident depends on the driver's effort but, should an accident occur, then the amount of losses is independent of it. Our analysis extends straightforwardly to the (more realistic case) where the risk-taking behavior also affects the probability distribution of damages, conditionally on an accident occurring. The probability distribution of $\tilde{y}_i$ depends on a parameter y, taken as its expected value, i.e. $y = E\tilde{y}_i$ for all i, and such that an increase in y corresponds to a first-order dominance shift in $\tilde{y}_i$[5].

Let $\tilde{\ }_i$ be the random cost of an accident to the at fault driver i and his or her family. $\tilde{\ }_i$ depends on $\tilde{y}_i$ and also on a random noise ε_i which reflects

[5] This assumption is quite strong but it is made for notational simplicity. More realistically, $E\tilde{y}_i$ may depend on parameters which are differentiated among drivers, such as the size of the family or the type of the car. The model could be easily extended in this direction by defining y as a parameter that affects the expected accident damages, i.e. $E\tilde{y}_i = \Phi_i(y)$, with $\Phi_i' > 0$.

the specificity of the accident. We write

$$\tilde{l}_i = \ell_i(\tilde{y}_i, \varepsilon_i)$$

with $\partial \ell_i / \partial \tilde{y}_i \geq 0$ where ε_i is a random variable which reflects the specificity of the accidents. Function $\ell_i(\tilde{y}_i, \varepsilon_i)$ implicitly depends on the insurance coverage. For instance, in case of a deductible, we have $\partial \ell_i / \partial \tilde{y}_i = 1$ for small $\tilde{y}_i$. Conversely, $\partial \ell_i / \partial \tilde{y}_i = 0$ if there is full insurance at the margin, and $0 < \partial \ell_i / \partial \tilde{y}_i < 1$ in case of coinsurance. Furthermore, the loss incurred by the driver also depends on the type of the accident. For instance, full liability insurance is usually required but drivers may have partial insurance for the damages to their own car. Likewise, there may be partial bodily injury insurance (or even no *pretium doloris* insurance) and full property insurance. The $\ell_i(.,.)$ function may differ among drivers, particularly when drivers buy different insurance policies with more or less generous coverage.

For the sake of simplicity, in this section and the following, functions $\ell_i(.,.)$ are taken exogenously given. In Section 4, we extend our results to the case where the insurance coverage is optimally modified in response to changes in the road transport system. Given $\ell_i(.,.)$ and ε_i, the probability distribution of $\tilde{l}_i$ depends on y and because $\partial \ell_i / \partial \tilde{y}_i \geq 0$, an increase in y entails a first-order dominance shift in $\tilde{l}_i$.

Let w_i be the wealth of driver i in the no-accident state. We have

$$w_i = \overline{w}_i - P_i - t_i \tag{1}$$

where $\overline{w}_i$ denotes driver i's initial wealth, P_i denotes the insurance premium and t_i is a (positive or negative) transfer paid by driver i to the government. $\overline{w}_i$ is taken as exogenously given. Determinants of P_i and t_i will be clarified in the next section.

We assume full liability of drivers for the damages they may inflict on other drivers. Hence, the final wealth of a driver is unaffected if he or she is the victim of an accident caused by another driver. From a descriptive standpoint, this is certainly an oversimplification of reality as it amounts to assuming that all damages can be compensated. We make this assumption since partial liability would make the modelling more cumbersome without any qualitative change in the results. Hence we have $w_i^f = w_i$ if driver i does not cause any accident and $w_i^f = w_i - \tilde{l}_i$ in the event of an accident caused by this driver. Driver i maximizes

$$[1 - p(e_i, x)]u_i(w_i) + p(e_i, x)E[u_i(w_i - \tilde{l}_i) \mid y] - e_i \tag{2}$$

with respect to $e_i \geq 0$.

Let $\hat{e}_i = \hat{e}_i(x; y; w_i)$ be the optimal level of effort chosen by the driver. Let $\Delta_i(y; w) = u_i(w_i) - E[u_i(w_i - \tilde{x}_i) | y]$. The first-order condition for the optimal choice of effort is

$$\frac{\partial p}{\partial e_i}(\hat{e}_i; x).\Delta_i(y; w_i) + 1 = 0 \tag{3}$$

if $\hat{e}_i > 0$, which will be assumed in what follows. Differentiating (3) gives

$$\frac{\partial \hat{e}_i}{\partial x} = -\frac{\partial^2 p / \partial e_i \partial x}{\partial^2 p / \partial e_i^2} \tag{4}$$

$$\frac{\partial \hat{e}_i}{\partial y} = -\frac{\partial p/\partial e_i \ \partial \Delta_i/\partial y}{\Delta_i(y; w_i)\partial^2 p/\partial e_i^2} \tag{5}$$

$$\frac{\partial \hat{e}_i}{\partial w_i} = -\frac{\partial p/\partial e_i \ \partial \Delta_i/\partial w_i}{\Delta_i(y; w_i)\partial^2 p/\partial e_i^2}. \tag{6}$$

We have $\Delta_i(y; w_i) > 0$ and $\partial\Delta_i/\partial y > 0$, which gives $\partial\hat{e}_i/\partial y > 0$. Furthermore $\partial\hat{e}_i/\partial x$ and $\partial^2 p/\partial e_i \partial x$ have opposite signs. We have $\partial\Delta_i/\partial w_i < 0$ if $u_i'' < 0$ and $\partial\Delta_i/\partial w_i = 0$ if $u_i'' = 0$. Hence for a risk-averse driver, an increase in w_i implies an decrease in $\Delta_i(y; w_i)$, thus a decrease in $\hat{e}_i$. Risk-neutral driver's behaviors are not affected by changes in w_i. Hence, the following proposition:

Proposition 1 ***For any driver i, the optimal effort level $\hat{e}_i$ is an increasing function of the expected cost of accidents, i.e. $\partial\hat{e}_i/\partial y > 0$. It is a decreasing function of the road safety parameter x when an increase in x reduces the marginal effect of the driver's effort on the probability of accident, i.e. $\partial\hat{e}_i/\partial x < 0$ if $\partial^2 p/\partial e_i \partial x > 0$.***

For a risk averse driver, the level of effort is decreasing with wealth, i.e. $\partial\hat{e}_i/\partial w_i < 0$. The behavior of risk neutral drivers is unaffected by changes in wealth.

Proposition 1 states that, ***ceteris paribus,*** safety measures that reduce the average cost of accidents result in a decrease in the effort level of drivers. The reason is quite obvious: the lower the average cost of accidents, the lower the expected marginal benefit (in utility terms) associated with an increase in the driver's effort level, hence a lower effort at equilibrium. According to Proposition 1, safety measures that reduce the probability of an accident entail a decrease in the effort level if they reduce the marginal decrease of the accident probability associated with an increase in effort, i.e. if $\partial p/\partial e_i$ decreases when x increases. In other words, the less safe the road transport system (in terms of accident probability, for a given behavior of drivers), the more useful an increase in effort (in terms of diminishing probability of accident). This seems to be a quite natural statement. Lastly, the effort level is negatively affected by a wealth effect when the driver is risk averse because in such a case the private cost of an accident (in utility terms) is decreasing with wealth.

Let

$$\hat{p}_i(x, y, w_i) = p(\hat{e}_i(x, y, w_i), x)$$

be the probability of an accident which follows from the driver's optimal behavior and from the road network parameters x and y. Proposition 1 gives $\partial \hat{p}_i/\partial y < 0$, $\partial \hat{p}_i/\partial w_i > 0$ if $u_i'' < 0$ and $\partial \hat{p}_i/\partial w_i = 0$ if $u_i'' = 0$. Furthermore, $\partial \hat{p}_i/\partial x$ may be negative or positive. In words, an increase in the expected cost of an accident or a decrease in the initial wealth of a risk averse individual lowers the probability of accident because of a more cautious driving. Conversely, one cannot maintain with certainty that an increase in the x parameter leads to a decrease in the probability of accident, since the beneficial direct effect of safer highways is offset by the behavioral adaptations of drivers. Hence, the sign of the total effect of x on p_i cannot be determined on theoretical grounds only: it is a matter of empirical analysis.

3 Cost-benefit analysis of road safety programs

It is sometimes argued that the behavioral adaptation affecting a road safety policy should be taken into account in appraising its desirability. For instance, according to the OECD expert group: "The potential for behavioral adaptation affecting a safety measure should be considered in estimating the costs and benefits of safety programs. Programs with minimal adaptation may be more effective, in the long run, than those which produce large initial safety gains, but also produce adaptations that eliminate the gain" (OECD, 1990, p. 118). While such a recommendation sounds intuitive and seems to make sense, it lets open the question of how and to what extent the behavioral adaptation effect should be taken into account in cost-benefit analysis.

A standard rule would recommend to compare the willingness to pay of road users for a safety measure to its cost. The users' willingness to pay may be derived indirectly, by estimating the effects of the measure in terms of human and non-human benefits (including the economic value of the decrease in the number of deaths and nonfatal accidents). How should the behavioral adaptation phenomenon be taken into account in this balance of costs and benefits?

To answer this question, we will insert the analysis of the previous section in a simple one-good model of optimal resource allocation under uncertainty and we will derive simple rules for optimal public decision making.

3.1 A simple model of optimal resource allocation

Insurers are supposed to offer insurance policies at actuarial fair premium. In case of an accident, the insurance indemnity is $\tilde{e}_i - \hat{e}_i$. Hence, we have

$$P_i = \hat{p}_i(x;y;w_i)[y - E(\tilde{e}_i \mid y)]. \tag{7}$$

The x, y parameters are affected by road safety programs. These programs entail public expenditures $C(x;y)$, with $\partial C/\partial x > 0$ and $\partial C/\partial y < 0$[6].

The government budget constraint is written as

$$\sum_{i=1} t_i = C(x;y). \tag{8}$$

Using (6), (7) and (8) gives

$$\sum_{i=1} w_i + \sum_{i=1} \hat{p}_i(x;y;w_i)[y - E(\tilde{e}_i \mid y)] + C(x;y) = \sum_{i=1} \overline{w}_i. \tag{9}$$

Let $V_i(w_i;x;y)$ be the optimal expected utility of driver i with

$$V_i(w_i;x;y) = \max_{e_i} \left\{[1 - p(e_i;x)]u_i(w_i) + p(e_i;x)E[u_i(w_i - \tilde{e}_i) \mid y] - e_i\right\}. \tag{10}$$

Note that the insurance indemnity schedule of driver i determines the probability distribution of $\tilde{e}_i$ and also the driver i's effort strategy $\hat{e}_i(x;y;w_i)$ and his or her probability of accident $\hat{p}_i(x;y;w_i)$. In this section we consider the insurance indemnity schedules as given and we characterize Pareto improving decision rules for road safety programs. In Section 4, we extend our analysis to the (more satisfactory) case where insurers optimally modify their insurance policy supply in response to changes in the safety of the road transport system.

[6] Note that a safety improvement increases x but reduces y.

The government chooses t_i (for $i = 1, \ldots, n$), x and y. Equivalently, the government chooses w_i (for $i = 1, \ldots, n$), x and y. A Pareto improving road safety policy corresponds to (infinitesimal) changes in the road transport system dx and dy and in the drivers' wealth levels dw_i, for $i = 1, \ldots n$ such that firstly the expected utility of all drivers is nondecreasing and it is increasing for at least one driver and, secondly the government budget constraint is satisfied. Let us first consider a ***prevention policy***, that is a policy which affects the x parameter.

The first condition may be written as

$$\frac{\partial V_i}{\partial w_i} dw_i + \frac{\partial V_i}{\partial x} dx \geq 0. \tag{11}$$

for all $i = 1, \ldots n$ with a strict inequality for at least one driver i. The second condition is

$$\sum_{i=1}^{n} \left[1 + \frac{\partial \tilde{\pi}_i}{\partial w_i}(y - E(\tilde{e}_i y))\right] dw_i + \sum_{i=1}^{n} \frac{\partial \tilde{\pi}_i}{\partial x}[y - E(\tilde{e}_i y)] dx + \frac{\partial C}{\partial x} dx = 0. \tag{12}$$

When $dx > 0$, there exist compensatory transfers dw_i for $i = 1, \ldots n$ such that (11) and (12) are satisfied if and only if

$$\sum_{i=1}^{n} \frac{\partial V_i / \partial x}{\partial V_i / w_i}\left[1 + \frac{\partial \tilde{\pi}_i}{\partial w_i}(y - E(\tilde{e}_i y))\right] - \sum_{i=1}^{n} \frac{\partial \tilde{\pi}_i}{\partial x}[y - E(\tilde{e}_i y)] > \frac{\partial C}{\partial x}. \tag{13}$$

(13) is the condition to be satisfied for an intensification of the prevention policy (i.e. an increase in x) to be welfare improving.

Likewise, a similar calculation shows that an intensification of the ***protection policy*** (i.e. a decrease in y) is welfare improving if and only if

$$-\sum_{i=1}^{n} \frac{\partial V_i / \partial y}{\partial V_i / w_i}\left[1 + \frac{\partial \tilde{\pi}_i}{\partial w_i}(y - E(\tilde{e}_i y))\right] + \sum_{i=1}^{n} \frac{\partial}{\partial y}[\tilde{\pi}_i (y - E(\tilde{e}_i y))] > -\frac{\partial C}{\partial y}. \tag{14}$$

(13) and (14) are cost-benefit decision rules.

The left-hand side and the right-hand side in (13) and (14) are respectively the marginal social value and the marginal cost of an increase in x or of a decrease in y. If the marginal social value exceeds the marginal cost, then an increase in x or a decrease in y is welfare improving. More precisely, such policies are potentially Pareto improving in the sense that, under (13) or (14), there exist possible compensatory transfers that make everyone as well off. In what follows, the distribution of tax burdens to pay for government safety projects is not specified, so the condition called (for the sake of brevity) "Pareto improvements" are actually potential Pareto improvement.

Let us consider a prevention policy. Set

$$WP_i^x = \frac{\partial V_i/\partial x}{\partial V_i/\partial w_i}$$

and

$$\overline{WP}_i^x = WP_i^x\left[1 + \frac{\partial \hat{\pi}_i}{\partial w_i}(y - E(\hat{\pi}_i y))\right].$$

WP_i^x is the marginal willingness to pay of driver i for an increase in x. $\overline{WP}_i^x$ is an adjusted marginal willingness to pay that takes into account the effect of w_i on insurance costs (due to adjustment in the insurance premium under a policy of full risk rating). When driver i is risk averse, this adjustment factor is larger than one because, in our model, an increase in driver i's wealth incites him to more risky driving (i.e. $\partial\hat{\pi}_i/\partial w_i > 0$ if $u_i'' < 0$ and $\partial\hat{\pi}_i/\partial w_i = 0$ if $u_i'' = 0$). We will refer to $\overline{WP}_i^x$ as the ***adjusted willingness to pay of driver i for the prevention policy***.

Let

$$I_i^x = -\frac{\partial \hat{\pi}_i}{\partial x}[y - E(\hat{\pi}_i y)]. \tag{15}$$

I_i^x is the decrease in expected insurance costs which results from an increase in x. I_i^x is positive under partial behavioral risk compensation i.e. when $\partial\hat{\pi}_i/\partial x < 0$. It would be negative when $\partial\hat{\pi}_i/\partial x > 0$, if there were overcompensation of the preventive measure through more risky driving.

Likewise, and with similar interpretations, let

$$WP_i^y = -\frac{\partial V_i/\partial y}{\partial V_i/w_i}$$

$$\overline{WP}_i^y = WP_i^y\left[1 + \frac{\partial \hat{\pi}_i}{\partial w_i}(y - E(\hat{\pi}_i y))\right]$$

and

$$I_i^y = \frac{\partial}{\partial y}[\hat{\pi}_i(y - E(\hat{\pi}_i y))].$$

Hence, rewriting (13) and (14) more compactly, we obtain the following result:

Proposition 2 ***A preventive road safety measure is Pareto improving if***

$$\sum_{i=1} \overline{WP}_i^x + \sum_{i=1} I_i^x > \frac{\partial C}{\partial x} \tag{16}$$

and a protective road safety measure is Pareto improving if

$$\sum_{i=1} \overline{WP}_i^y + \sum_{i=1} I_i^y > -\frac{\partial C}{\partial y}. \tag{17}$$

Proposition 2 says that a road safety measure (be it preventive or protective) is Pareto improving if its marginal cost is lower than the corresponding sum of the drivers'adjusted marginal willingness to pay for such a measure and of the reduction in insurance costs.

3.2 Estimating the drivers' willingness to pay for a road safety measure

However, it is unlikely that the drivers' (adjusted) marginal willingness to pay for a road safety measure will be easily observed by the Government: this may be considered as an hidden information privately hold by drivers. The conditions in Proposition 2 are thus of little help unless we turn them into equivalent (or approximately equivalent) criteria that do not depend too heavily on such an hidden information. Fortunately, we can connect the driver's marginal willingness to pay for a safety measure to the effects of this measure on losses. Let us consider first a prevention measure. Assume that driver i is risk neutral. Then, using the envelope theorem gives

$$WP_i^x = -\frac{\partial p}{\partial x}(\hat{e}_i; x)E(\tilde{\ell}_i\, y). \tag{18}$$

Hence, under risk neutrality, the marginal willingness to pay for a prevention measure affecting the highways is equal to the decrease in non-insured expected accidents costs, for an unchanged effort level (no adjustment is required because there is no wealth effect on insurance cost when the driver is risk neutral). In other words, the behavioral adaptation should ***not*** be taken into account in estimating the private benefits of the safety measure. On the contrary, (15) shows that the behavioral adaptation should be considered in estimating the benefits which correspond to lower insured damages. The reason for this asymmetry is the fact that (at the first order) the increase in uninsured losses exactly corresponds to the drivers' lower effort disutility. A better transport system allows road users to enjoy a more reckless driving or a faster speed. When drivers choose their effort optimally, this welfare effect is just compensated (at the first order) by the increase in expected uninsured damages due to the change in the effort level.

Assume now that driver i is risk averse. Using the envelope theorem then gives,

$$WP_i^x = \frac{\partial p}{\partial x}(\hat{e}_i; x)\frac{u_i(w_i) - E[u_i(w_i - \tilde{d}_i) \mid y]}{(1 - p_i)u_i'(w_i) + p_i E[u_i'(w_i - \tilde{d}_i) \mid y]} \tag{19}$$

where $p_i \equiv p(\hat{e}_i; x)$. Using (19) allows us to show that, if the probability of an accident is not too large, then the marginal willingness to pay of a risk-averse driver for an increase in x is larger than the corresponding decrease in his expected uninsured damages with unchanged behavior. This is established in the following lemma[7].

Lemma 1 ***Assume*** $M_i < u_i''(w) < m_i < 0$ ***for all*** w***. Then***

$$\frac{\partial V_i/\partial x}{\partial V_i/\partial w_i} > -\frac{\partial p}{\partial x}(\hat{e}_i; x)E(\tilde{d}_i \mid y) \quad \textit{if} \quad 0 \leq p_i \leq \frac{m_i}{M_i + m_i}.$$

Proof: see the appendix.

Lemma 1 can be interpreted as follows. Assume that the effort of driver i is fixed at its optimal level $e_i = \hat{e}_i$ and consider a small variation dx. Let

$$dt_i^* = -\frac{\partial p}{\partial x}(\hat{e}_i; x)E(\tilde{d}_i \mid y)dx$$

be a transfer from driver i to the government which compensates for the variation in the accident probability $dp_i = [\partial p(\hat{e}_i; x)/\partial x]dx$ in such a way that driver i's expected wealth is kept constant. Hence $(dx; dt_i^*)$ induces a mean preserving variation in driver i's wealth. Assume $dx < 0$, which gives $dp_i > 0$. Such a change puts more weight on the "accident" state and less weight on the "no-accident" state. It is in fact a mean preserving spread in the sense of Rothschild and Stiglitz (1970) if the probability of the "accident" state is not too large. Otherwise, it would be a mean preserving contraction. Driver i is negatively affected by a mean preserving spread in his (or her) wealth because he (or she) is risk averse. Hence, if p_i is not too large, the net

[7] Note that more restrictive conditions on $u_i(\cdot)$ would allow to relax the upper bound on p_i under which the inequality of Lemma 1 holds. In particular, if $u_i(\cdot)$ exhibits ***mixed risk aversion*** in the sense of Caballé and Pomansky (1996), then as shown by Dachraoui et alii (2000), the inequality of Lemma 1 holds if $p_i < 1/2$.

transfer to driver i denoted by dw_i which would exactly compensate for the utility loss induced by the increase in the accident probability is such that $dw_i \geq -dt_i^*$, which implies

$$\frac{dw_i}{dx} \geq -\frac{\partial p}{\partial x}(\hat{e}_i; x)E(\tilde{\ell}_i | y).$$

This gives a lower bound for the marginal willingness to pay for an increase in x, when $\hat{e}_i$ is fixed at its optimal level. Because of the envelope theorem, the fact that driver i optimally modifies his or her effort level in response to changes in x does not change the result.

Using (19) also allows us to get an estimate of the marginal willingness to pay for a prevention measure when p_i is small. Indeed, we have

$$\lim_{p_i \to 0} WP_i^x \times \frac{1}{\frac{\partial p}{\partial x}(\hat{e}_i; x)} = \frac{u_i(w_i) - E[u_i(w_i - \tilde{\ell}_i) | y]}{u_i'(w_i)}. \tag{20}$$

Using a second-order Taylor expansion gives

$$E[u_i(w_i - \tilde{\ell}_i) | y] \simeq u_i(w_i) - u_i'(w_i)E(\tilde{\ell}_i | y) + \frac{1}{2}u_i''(w_i)E(\tilde{\ell}_i^2 | y). \tag{21}$$

(20) and (21) then yield

$$\lim_{p_i \to 0} WP_i^x \times \frac{1}{\frac{\partial p}{\partial x}(\hat{e}_i; x)} \simeq E(\tilde{\ell}_i | y)\left[1 + \frac{R_i(w_i)E(\tilde{\ell}_i^2 | y)}{2w_i E(\tilde{\ell}_i | y)}\right] \tag{22}$$

where $R_i(w_i) \equiv -w_i u_i''(w_i)/u_i'(w_i)$ is the coefficient of relative risk aversion.

As an example, assume $\tilde{\ell}_i \rightsquigarrow Exp(\lambda)$, with $\lambda^{-1} = E(\tilde{\ell}_i | y)$. We then have $E(\tilde{\ell}_i^2 | y)/E(\tilde{\ell}_i | y) = 2E(\tilde{\ell}_i | y)$. Assume furthermore $\lambda^{-1} = \$1000$, $w_i = \$25000$ and $R_i(w_i) \in [1; 4]$[8]. We then have

$$\frac{R_i(w_i)E(\tilde{\ell}_i^2 | y)}{2w_i E(\tilde{\ell}_i | y)} \in [0.04\ ;\ 0.16]$$

which suggests that, in practice, the difference

$$WP_i^x - \frac{\partial p}{\partial x}(\hat{e}_i; x)E(\tilde{\ell}_i | y)$$

is probably small for reasonable estimates of the coefficient of relative risk aversion.

[8] See Gollier (2001, p31) on why a coefficient of relative risk aversion between 1 and 4 is a reasonable assumption.

Hence we may write

$$WP_i^x = -\theta_i^1 \frac{\partial p}{\partial x}(\hat{e}_i; x) E(\tilde{\ell}_i \mid y) \tag{23}$$

with $\theta_i^1 = 1$ if driver i is risk neutral and $\theta_i^1 > 1$ if he (or she) is risk averse (with reasons to think that, on real data, the difference between θ_i^1 and 1 is probably not very large).

Likewise, using the envelope theorem gives:

$$WP_i^y = -\frac{\partial V_i / \partial y}{\partial V_i / \partial w_i} = p(\hat{e}_i; x) \frac{\partial E(\tilde{\ell}_i \mid y)}{\partial y} \tag{24}$$

if driver i is risk neutral. In words, under risk neutrality, the marginal willingness to pay for a protection measure affecting the highways is equal to the decrease in noninsured expected accident costs for an unchanged driving behavior. When driver i is risk averse, we have

$$-\frac{\partial V_i / \partial y}{\partial V_i / \partial w_i} = p_i \frac{\frac{\partial}{\partial y} E[u_i(w_i - \tilde{\ell}_i) \mid y]}{(1 - p_i) u_i'(w_i) + p_i E[u_i'(w_i - \tilde{\ell}_i) \mid y]} \tag{25}$$

where $p_i = p(\hat{e}_i; x)$.

Lemma 2 ***Assume that*** $\tilde{\ell}_i$ ***is distributed on*** $[0; \bar{y}]$, $\bar{y} > 0$, ***according to a density function*** $f(\tilde{\ell}_i \mid y)$. ***Let*** $F(\tilde{\ell}_i \mid y)$ ***denote the corresponding cumulative distribution function. Assume that*** $u_i'' < 0$ ***and that*** $\dfrac{\frac{\partial F}{\partial y}(\tilde{\ell}_i \mid y)}{f(\tilde{\ell}_i \mid y)}$ ***is non-increasing with respect to*** $\tilde{\ell}_i$. ***Then***

$$-\frac{\partial V_i / \partial y}{\partial V_i / \partial w_i} > p_i \frac{\partial E(\tilde{\ell}_i \mid y)}{\partial y}$$

Proof: See the appendix.

Lemma 2 provides a condition under which the willingness to pay of a risk averse driver for an intensification in the protection policy (i.e. for a decrease in y) is larger than the corresponding decrease in expected uninsured accident costs, for an unchanged driving effort level. The intuitive meaning of this condition is as follows. Let us remind that an increase in y shifts the distributions of $\tilde{y}$ and $\tilde{\beta}$ in the sense of first-order stochastic dominance. Consider a decrease in y, which gives a decrease in the average cost of accidents. Because the marginal utility of wealth is decreasing, the willingness to pay of a risk averse driver for such a protection policy will be higher when this policy lowers the probability of the most serious accidents than when it reduces the gravity of minor accidents. In Lemma 2, we make an assumption to express the fact that the protection policy affects more intensely the most serious accidents (i.e. the accidents with large damages, particularly fatalities) than the accidents with slight material damages. In mathematical terms, we postulate that, following an increase in y, the rightward shift of the cumulative distribution $F(\beta_i \mid y)$—if we measure it horizontally— is nondecreasing with β_i. This is true if $\frac{\partial F}{\partial y}(\beta_i \mid y)/f(\beta_i \mid y)$ is non-increasing in β_i which is assumed in what follows.

As an illustration, we may get an estimate of the marginal willingness to pay for a protection measure when p_i is small and $\tilde{\beta}_i \rightsquigarrow \mathrm{Exp}(\lambda)$, with $\lambda^{-1} = E(\tilde{\beta}_i \mid y)$. We have

$$\lim_{p_i \to 0} WP_i^y \times \frac{1}{p_i} = \frac{\frac{\partial}{\partial y} E[u_i(w_i - \beta_i) \mid y]}{u_i'(w_i)} \tag{26}$$

and a simple calculation gives

$$\frac{\partial}{\partial y} E[u_i(w_i - \beta_i) \mid y] = \frac{\frac{\partial E(\beta_i \mid y)}{\partial y}}{E(\tilde{\beta}_i \mid y)} \int_0^{+\infty} u_i'(w_i - \beta_i)\beta_i f(\beta_i \mid y) d\beta_i.$$

Using a second order Taylor expansion of $u_i'(w_i - \beta_i)$ around $u_i'(w_i)$ then yields

$$\frac{\frac{\partial}{\partial y} E[u_i(w_i - \beta_i) \mid y]}{u_i'(w_i)} \simeq \frac{\partial E(\beta_i \mid y)}{\partial y}\left[1 + \frac{R_i(w_i) E(\tilde{\beta}_i \mid y)}{w_i}\right]. \tag{27}$$

Hence, for instance, when $\lambda^{-1} = \$1000$, $w_i = \$25000$ and $R_i(w_i) \in [1, 4]$, we get

$$1.04 \times p_i \frac{\partial E(\beta_i \mid y)}{\partial y} \leq WP_i^y \leq 1.16 \times p_i \frac{\partial E(\beta_i \mid y)}{\partial y}.$$

Of course, we should not give too much importance to such an example but once again it suggests that the adjustment of the marginal willingness to pay due to risk aversion is probably small.

Hence we may write

$$WP_i^y = \theta_i^2 p_i \frac{\partial \mathbf{E}(\tilde{\ }_i\, y)}{\partial y}$$

with $\theta_i^2 = 1$ under risk neutrality and $\theta_i^2 > 1$ under risk aversion. These results are summarized in the following proposition:

Proposition 3 ***Under the assumptions made in Lemmas 1 and 2, we have***

$$WP_i^x = -\theta_i^1 \frac{\partial p}{\partial x}(\hat{e}_i; x)\mathbf{E}(e_i\, y) \tag{28}$$

$$WP_i^y = \theta_i^2 p_i \frac{\partial \mathbf{E}(\tilde{\ }_i\, y)}{\partial y} \tag{29}$$

with $\theta_i^1 = \theta_i^2 = 1$ ***if driver*** i ***is risk neutral and*** $\theta_i^1 > 1$ ***and*** $\theta_i^2 > 1$ ***if he (or she) is risk averse.***

3.3 Cost-benefit criteria

Proposition 3 allows us to rewrite the total marginal benefits of road safety measures in a more explicit way. Using (28) gives

$$\begin{aligned}\sum_{i=1} \overline{WP}_i^x + \sum_{i=1} I_i^x &= -\sum_{i=1} \theta_i^1 \frac{\partial p}{\partial x}(\hat{e}_i; x)\mathbf{E}(e_i\, y)[1 + \frac{\partial \hat{p}_i}{\partial w_i}(y - \mathbf{E}(e_i\, y))] \\ &\quad - \sum_{i=1} \frac{\partial \hat{p}_i}{\partial x}[y - \mathbf{E}(\tilde{\ }_i\, y)]\end{aligned}$$

$$\begin{aligned}&= \sum_{i=1} [y + (\theta_i^1 - 1)\mathbf{E}(\tilde{\ }_i\, y)]\frac{\partial p}{\partial x}(\hat{e}_i; x) \\ &\quad - \sum_{i=1} \frac{\partial p}{\partial e}(\hat{e}_i; x)[\frac{\partial \hat{e}_i}{\partial x}(x; y; w) + \theta_i^1 \frac{\partial p}{\partial x}(\hat{e}_i; x)\mathbf{E}(e_i\, y)\frac{\partial \hat{e}_i}{\partial w_i}(x; y; w)][y - \mathbf{E}(\tilde{\ }_i\, y)]\end{aligned} \tag{30}$$

and using (29) gives

$$\begin{aligned}\sum_{i=1} \overline{WP}_i^y + \sum_{i=1} I_i^y &= \sum_{i=1} [\theta_i^2 p_i \frac{\partial \mathbf{E}(\tilde{\ }_i\, y)}{\partial y}][1 + \frac{\partial \hat{p}_i}{\partial w_i}(y - \mathbf{E}(e_i\, y))] \\ &\quad + \sum_{i=1} p_i[1 - \frac{\partial \mathbf{E}(\tilde{\ }_i\, y)}{\partial y}] + \sum_{i=1} \frac{\partial}{\partial y}[\hat{p}_i(y - \mathbf{E}(e_i\, y))]\end{aligned}$$

$$= \sum_{i=1} [1 + (\theta_i^2 - 1)\frac{\partial E(\tilde{\ }_i\, y)}{\partial y}]\, p(e_i; x)$$

$$+ - \sum_{i=1} \frac{\partial p}{\partial e}(\hat{e}_i; x)[\frac{\partial \hat{e}_i}{\partial y}(x; y; w) + \theta_i^2 p_i \frac{\partial E(\tilde{\ }_i\, y)}{\partial y}\frac{\partial \hat{e}_i}{\partial w_i}(x; y; w)][y - E(\tilde{\ }_i\, y)] \tag{31}$$

Hence the following Proposition:

Proposition 4 ***A preventive road safety measure is Pareto-improving if and only if***

$$-\sum_{i=1} [y + (\theta_i^1 - 1)E(\tilde{\ }_i\, y)]\frac{\partial p}{\partial x}(\hat{e}_i; x) - \sum_{i=1} \Delta_i^x \frac{\partial p}{\partial e}(\hat{e}_i; x)[y - E(\tilde{\ }_i\, y)] > \frac{\partial C}{\partial x} \tag{32}$$

where

$$\Delta_i^x = \frac{\partial \hat{e}_i}{\partial x}(x; y; w) + \theta_i^1 \frac{\partial p}{\partial x}(\hat{e}_i; x) E(\tilde{e}_i\, y) \frac{\partial \hat{e}_i}{\partial w_i}(x; y; w). \tag{33}$$

A protective road safety measure is Pareto-improving if and only if

$$\sum_{i=1} p_i [1 + (\theta_i^2 - 1)\frac{\partial E(\tilde{\ }_i\, y)}{\partial y}] + \sum_{i=1} \Delta_i^y \frac{\partial p}{\partial e}(\hat{e}_i; x)[y - E(\tilde{e}_i\, y)] > -\frac{\partial C}{\partial y} \tag{34}$$

where

$$\Delta_i^y = \frac{\partial \hat{e}_i}{\partial y}(x; y; w) + \theta_i^2 p_i \frac{\partial E(\tilde{\ }_i\, y)}{\partial y}\frac{\partial \hat{e}_i}{\partial w_i}(x; y; w). \tag{35}$$

The first term in the left hand side of (32) is the direct marginal welfare effect of a prevention measure with unchanged behaviors. For each driver, this direct effect is the sum of the decrease in the total losses which results from a unit increase in x with unchanged behaviors (i.e. $-y\partial p/\partial x$) and of an adjustment term which is positive in case of risk aversion. This adjustment term is equal to $-(\theta_i^1 - 1)\, E(\tilde{\ }_i\, y)\partial p/\partial x$ with $\theta_i^1 = 1$ or > 1 depending on whether driver i is risk neutral or risk averse. It gives a positive social value to the decrease in uninsured losses incurred by risk averse drivers. This first term may be called the ***adjusted direct welfare gain of the prevention measure***. The second term in the left hand side of (32) is the increase in insured losses following a unit increase in x, because of drivers' behavioral adaptation. Indeed, observe that $\Delta_i^x dx$ is the effort variation resulting from an infinitesimal variation dx. This effort variation includes the direct effect $\partial \hat{e}_i/\partial x$ and the (adjusted for risk aversion) wealth effect $\theta_i^1 E(\tilde{\varepsilon}_i y)[\partial p(\hat{e}_i; x)/\partial x]\partial \hat{e}_i/\partial w_i$ due to the change in the uninsured losses. Note that this wealth effect vanishes if driver i is risk neutral, since $\partial \hat{e}_i/\partial w_i = 0$ in such a case. Multiplying this effort variation Δ_i^x by $[\partial p(\hat{e}_i; x)/\partial e][y - E(\tilde{\varepsilon}_i y)]$ gives the effect of behavioral adaptation on insured losses. In a word, the first part of Proposition 4 says that a more intensive prevention policy (associated with adequately chosen compensatory transfers) is Pareto improving when its marginal cost is lower than the difference between the adjusted direct welfare gain and the effect of behavioral adaptation on insured losses.

Note that a conventional cost-benefit study would usually identify the benefits of a prevention measure with the first term only, probably ignoring the adjustment for risk aversion. This is usually done by estimating the decrease in human or non-human losses that would have been possible in given circumstances (particularly with given driving behaviors) if the prevention measure had been previously adopted. Extrapolating the results from these case studies to the whole road transport system would allow the public decision maker to appraise the desirability of a prevention measure. Our results show that the additional expected insured losses resulting from behavioral adaptation should be deduced from the previous estimate of net benefits of a traffic safety policy.

The second part of Proposition 4 can be rephrased in similar terms. Indeed $p_i[1 + (\theta_i^2 - 1)\partial E(\tilde{\varepsilon}_i y)/\partial y]\, dy$ is the ***adjusted direct welfare gain of the protection measure*** dy ***for driver*** i and $\Delta_i^y[\partial p(\hat{e}_i; x)/\partial e][y - E(\tilde{\varepsilon}_i y)]dy$ is the effect of behavioral adaptation on insured losses, with $\Delta_i^y dy$ the induced effort variation. Hence, Proposition 4 says that a more intensive protection policy is Pareto-improving if its marginal cost is less than the difference between the adjusted welfare gain and the effect of behavioral adaptation on insured losses.

4 Optimal insurance contracting

Thus far, for the sake of simplicity, we have assumed that the drivers' insurance indemnity schedules were exogenously given. However, the changes in the road transport system may affect the characteristics of the insurance policies (not only the premium as in the previous section, but also the indemnity schedule). We will now show that the results derived in the previous section can be extended to the case where the insurance contracts are modified in reaction to the changes in the traffic safety. In other words, we endogenize the determination of the insurance contracts.

Let us assume that, in the event of an accident, the total losses $\tilde{y}_i$ include insurable losses $\tilde{y}_{1i}$ and uninsurable losses $\tilde{y}_{2i}$. Hence, we have $\tilde{y}_i = \tilde{y}_{1i} + \tilde{y}_{2i}$. The probability distribution of $\tilde{y}_{1i}$ and $\tilde{y}_{2i}$ depend on $y = E\tilde{y}_i$. x and y are still taken as indicators of the quality of highways in terms of traffic safety. The insurance market is supposed to be competitive and drivers are risk-averse. Let $(P_i, q_i(.))$ be the insurance policy which is bought by driver i, where $q_i(\tilde{y}_{1i})$ is the indemnity schedule and P_i is the premium. The insurance contract of a given driver is the solution of a standard optimal contracting problem under moral hazard. Driver i maximizes

$$[1 - p(e_i, x)]u_i(\bar{w}_i - P_i - t_i) + p(e_i, x)E[u_i(\bar{w}_i - P_i - t_i - \tilde{y}_{1i} - \tilde{y}_{2i} + q_i(\tilde{y}_{1i})) \mid y] - e_i$$

with respect to $P_i, q_i(\tilde{y}_{1i}) \geq 0$ and e_i subject to

$$P_i \geq p(e_i, x)\ E[q_i(\tilde{y}_{1i}) \mid y] \tag{36}$$

and

$$\frac{\partial p}{\partial e}(e_i, x)[u_i(\bar{w}_i - P_i - t_i) - E(u_i(\bar{w}_i - P_i - t_i - \tilde{y}_{1i} - \tilde{y}_{2i} + q_i(\tilde{y}_{1i})) \mid y)] = -1. \tag{37}$$

In this problem, (36) is the break-even constraint: it ensures that the insurers would willingly offer the contract. (37) is the incentive compatibility constraint: it ensures that the effort level e_i will actually be chosen by driver i under the incentives provided by the insurance policy.

Let $\bar{V}_i(t_i, x, y)$ be the expected utility of driver i under the optimal insurance contract. It is important to observe that the effect of a change in x or y on P_i is taken into account by the derivatives $\partial\bar{V}_i/\partial x$ or $\partial\bar{V}_i/\partial y$. This was not the case for $\partial V_i/\partial x$ and $\partial V_i/\partial y$ in the previous section.

The government budget constraint is still written as (8). A prevention measure dx is Pareto improving if there exist dt_i, for $i = 1, ...n$, such that

$$\frac{\partial\bar{V}_i}{\partial t_i}dt_i + \frac{\partial\bar{V}_i}{\partial x}dx \geq 0 \tag{38}$$

for all $i = 1, ...n$ with a strict inequality for at least one driver i and

$$\sum_{i=1} dt_i + \frac{\partial C}{\partial x}dx = 0. \tag{39}$$

Equivalently, the measure is Pareto improving if

$$-\sum_{i=1} \frac{\partial\bar{V}_i/\partial x}{\partial\bar{V}_i/\partial t_i} > \frac{\partial C}{\partial x}. \tag{40}$$

Let α and β denote the Lagrange multipliers associated with (36) and (37) in the previous problem, with $\alpha \geq 0$. Using (37), the first-order optimality condition on e_i gives

$$\alpha \frac{\partial p}{\partial e_i} Eq_i = \beta \frac{\partial^2 p}{\partial e_i^2}(u_{io} - Eu_{i1}) \tag{41}$$

where $Eq_i \equiv E[q_i(\tilde{y}_{1i})|y]$, $u_{io} \equiv u_i(\bar{w}_i - P_i - t_i)$ and $Eu_{i1} \equiv E[u_i(\bar{w}_i - P_i - t_i - \tilde{y}_{1i} - \tilde{y}_{2i} + q_i(\tilde{y}_{1i}))|y]$. Note that (37) gives $u_{io} > Eu_{i1}$ and that (41) gives $\beta \leq 0$[9]. The optimality condition on P_i gives

$$\alpha = (1 - p_i)u'_{io} + p_i Eu'_{i1} + \beta \frac{\partial p}{\partial e_i}(u'_{io} - Eu'_{i1}) \tag{42}$$

where $u'_{io} \equiv u'_i(\bar{w}_i - P_i - t_i)$ and $Eu'_{i1} \equiv E[u'_i(\bar{w}_i - P_i - t_i - \tilde{y}_{1i} - \tilde{y}_{2i} + q_i(\tilde{y}_{1i}))|y]$. Using the envelope theorem and (42) then yield

$$\frac{\partial \bar{V}_i}{\partial t_i} = -\alpha \tag{43}$$

and

$$\frac{\partial \bar{V}_i}{\partial x} = (u_{io} - Eu_{i1})[\beta \frac{\partial^2 p}{\partial e_i \partial x} - \frac{\partial p}{\partial x}(e_i, x)] - \alpha E q_i \frac{\partial p}{\partial x}(e_i, x). \tag{44}$$

Let $\hat{e}_i(x, y, w_i)$ be the effort level induced by the optimal insurance contract. The partial derivatives of $\hat{e}_i$ are still given by (4),(5) and (6), with $\Delta_i(y, w_i) = u_{io} - Eu_{i1}$ and $\tilde{\epsilon}_i = \tilde{y}_{1i} + \tilde{y}_{2i} - q_i(\tilde{y}_{1i})$. Note that $\partial \Delta_i(y, w_i)/\partial w_i = u'_{io} - Eu'_{i1}$ and that $E\tilde{\epsilon}_i = y - Eq_i$. (4),(41), (43) and (44) yield

$$-\frac{\partial \bar{V}_i/\partial x}{\partial \bar{V}_i/\partial t_i} = -\frac{\partial p}{\partial x}(Eq_i + \frac{u_{io} - Eu_{i1}}{\alpha}) - \frac{\partial p}{\partial e_i}\frac{\partial \hat{e}_i}{\partial x} Eq_i \tag{45}$$

where $\partial p/\partial x$ and $\partial p/\partial e_i$ are evaluated at $e_i = \hat{e}_i$. Using (6),(41) and (42) give

$$\alpha = \frac{(1 - p_i)u'_{io} + p_i Eu'_{i1}}{1 + Eq_i \frac{\partial p}{\partial e_i}\frac{\partial \hat{e}_i}{\partial w_i}}. \tag{46}$$

[9] The optimality condition on $q_i(\tilde{y}_{1i})$ would allow us to show that $\beta < 0$, but this is useless to establish the cost-benefit rule.

Substituting the value of α given by (46) into (45) gives

$$-\frac{\partial \bar{V}_i/\partial x}{\partial \bar{V}_i/\partial t_i} = -\frac{\partial p}{\partial x}\left[Eq_i + \frac{u_{i0} - Eu_{i1}}{(1-p_i)u'_{i0} + p_i Eu'_{i1}} \times \left(1 + Eq_i \frac{\partial p}{\partial e_i}\frac{\partial \hat{e}_i}{\partial w_i}\right)\right] - \frac{\partial p}{\partial e_i}\frac{\partial \hat{e}_i}{\partial x} Eq_i. \tag{47}$$

When p_i is small, we know from (19) and Lemma 1 that we may write

$$\frac{u_{i0} - Eu_{i1}}{(1-p_i)u'_{i0} + p_i Eu'_{i1}} = \theta_i^1 (y - Eq_i) \tag{48}$$

with $\theta_i^1 > 1$ if driver i is risk averse. Using (47), (48) and $E\tilde{e}_i = y - Eq_i$ then gives

$$\begin{aligned} -\frac{\partial \bar{V}_i/\partial x}{\partial \bar{V}_i/\partial t_i} &= -\theta_i^1 \frac{\partial p}{\partial x} E\tilde{e}_i \left[1 + (y - E\tilde{e}_i)\frac{\partial p}{\partial e_i}\frac{\partial \hat{e}_i}{\partial w_i}\right] \\ &\quad -\left(\frac{\partial p}{\partial x} + \frac{\partial p}{\partial e_i}\frac{\partial \hat{e}_i}{\partial x}\right)(y - E\tilde{e}_i) \end{aligned}$$

Finally, we obtain

$$-\frac{\partial \bar{V}_i/\partial x}{\partial \bar{V}_i/\partial t_i} = -\frac{\partial p}{\partial x}\left[y + (\theta_i^1 - 1)E\tilde{e}_i\right] - \Delta_i^x \frac{\partial p}{\partial e}(y - E\tilde{e}_i) \tag{49}$$

where Δ_i^x is defined as in Proposition 4. Using (49) shows that (32) and (39) coincide. In other words, the cost-benefit criterion defined in Proposition 4 is still valid when drivers choose optimal insurance contracts in response to change in the road transport system. A similar result could be derived in the same way for a protection policy.

5 Conclusion

It is often argued that ignoring the behavioral adaptation of drivers would bias the cost-benefit analysis of a road safety measure toward positive net benefits of an active traffic safety regulation. However, the way in which behavioral adaptations should be taken into account in the balance of costs and benefits is not self-evident. The purpose of this paper was to clarify this issue of how behavioral adaptation should affect conventional cost-benefit analysis in the framework of a simple model of resource allocation under uncertainty. In the end, we got a rather simple result: the net benefits of a road safety policy are written as the difference between the (adjusted for risk aversion) reduction of total losses under unchanged behaviors and the increase in insured losses attributable to behavioral adaptation. Furthermore, the same kind of formula applies to prevention measures as to protection policies.

Such a cost-benefit criterion allows the policymaker to appraise the desirability of additional public investments for highways, but it can also be used for new mandatory automobile safety devices, be they preventive (e.g. antilocking systems) or protective (e.g. seat belts, crash tests,...). Among other possible extensions, we may also note that, in practice, behavioral adaptation to road safety policy also goes through an increase in traffic density, which may induce externalities in the form of congestion costs or of an increase in average accident risk. Furthermore, accidents may also be costly for the drivers not at fault, particularly in case of bodily injuries. Although the main objectives of this paper were of a theoretical nature, taking these effects into account would put our analysis back in a more realistic framework. This would certainly be essential for the purpose of implementation on real data.

Note finally that the results derived in this paper suggest that there exists some kind of substitutability between private protection from accident risks through insurance and public protection through tax financed expenditures or mandatory safety devices. When agents are more completely insured against accident losses, the social cost of behavioral adaptation is higher and, in such a case, the social value of a more active safety regulation is lower.

APPENDIX

Proof of Lemma 1

For ℓ_i fixed, the Taylor inequalities give:

$$\begin{cases} u_i(w_i) - u_i(w_i - \ell_i) \geq u_i'(w_i) - \frac{\ell_i^2}{2} m_i \\ u_i(w_i) - u_i(w_i - \ell_i) \geq \ell_i u_i'(w_i - \ell_i) + \frac{\ell_i^2}{2} M_i \end{cases}$$

Hence

$$\begin{aligned} u_i(w_i) - u_i(w_i - \ell_i) &\geq \ell_i((1-p)u_i'(w_i) + pu'(w_i - \ell_i)) + \frac{\ell_i^2}{2}(pM_i - (1-p)m_i) \\ &\geq \ell_i^2((1-p)u_i'(w_i) + pu'(w_i - \ell_i^2)). \end{aligned}$$

Since $u'(w_i - \ell_i)$ is increasing in ℓ_i, both random variables $\tilde{\ell}_i$ and $u'(w_i - \tilde{\ell}_i)$ are positively correlated. Therefore, we may write

$$E[\tilde{\ell}_i u'(w_i - \tilde{\ell}_i) | y] \geq E[\tilde{\ell}_i | y] E[u'(w_i - \tilde{\ell}_i) | y]$$

and

$$u_i(w_i) - E[u_i(w_i - \tilde{\ell}_i) | y] \geq E[\tilde{\ell}_i | y] E[(1-p)u_i'(w_i) + pu'(w_i - \tilde{\ell}_i) | y].$$

Finally, (20) gives the result. ■

Proof of Lemma 2

We have

$$E[u_i(w_i - \tilde{\ell}_i) | y] = \int_0^{\bar{y}} u_i(w_i - \tilde{\ell}_i) f(\tilde{\ell}_i | y) d\tilde{\ell}_i.$$

Integrating by parts gives

$$E[u_i(w_i - \tilde{\ell}_i) | y] = u_i(w_i - \bar{y}) - \int_0^{\bar{y}} u_i'(w_i - \tilde{\ell}_i) F(\tilde{\ell}_i | y) d\tilde{\ell}_i.$$

We may write

$$\frac{\partial E[u_i(w_i - \tilde{\ell}_i) | y]}{\partial y} = -\int_0^{\bar{y}} u_i'(w_i - \tilde{\ell}_i) \frac{\partial F(\tilde{\ell}_i | y)}{\partial y} d\tilde{\ell}_i.$$

Assuming that $\dfrac{\frac{\partial F}{\partial y}(e_i|y)}{f(e_i|y)}$ is non-increasing in e_i, we have

$$\frac{\partial \mathbf{E}[u_i(w_i - e_i)|y]}{\partial y} \geq -\int_0^{\bar{y}} u_i'(w_i - e_i) f(e_i|y) de_i \int_0^{\bar{y}} \frac{\partial F(e_i|y)}{\partial y} de_i$$

because $u_i'(w_i - e_i)$ and $\dfrac{\frac{\partial F}{\partial y}(e_i|y)}{f(e_i|y)}$ are positively correlated random variables. Hence we have

$$\frac{\partial \mathbf{E}[u_i(w_i - e_i)|y]}{\partial y} \geq \mathbf{E}[u_i'(w_i - e_i)|y] \frac{\partial}{\partial y} \mathbf{E}(e_i|y).$$

Using (25) then gives

$$\begin{aligned} -\frac{\partial V_i/\partial y}{\partial V_i/\partial w_i} &\geq \frac{p_i \mathbf{E}[u_i'(w_i - e_i)|y] \frac{\partial}{\partial y} \mathbf{E}(e_i|y)}{(1 - p_i) u_i'(w_i) + p_i \mathbf{E}[u_i'(w_i - e_i)|y]} \\ &> p_i \frac{\partial}{\partial y} \mathbf{E}(e_i|y) \end{aligned}$$

because

$$\mathbf{E}[u_i'(w_i - e_i)|y] > u_i'(w_i). \qquad \blacksquare$$

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