New Safety Technologies and Vehicle Safety

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Abstract

There has been a significant amount of research, especially empirical, on the effects that vehicle safety technologies such as seatbelts and airbags have on driver behaviour and resulting accindent rates. In this paper we investigate the impact of vehicle safety technologies which either reduce the probability of an accident or the size of loss associated with an accident should one occur. We do this in an environment with heterogeneous individuals who differ either by their (subjective) cost of taking effort to avoid accidents or by their (subjective) size of loss should an accident occur. We investignate both selection effects (i.e., who will value more highly the technology and so purchase it) and the effect on driving behaviour. The latter is the so-called offsetting or risk compensation effect. Using a data set that combines information from two sources: one about equipment levels of vehicles and the other from insurance experience (i.e., accidents, changes in bonus malus) we investigate the effects of selection (adverse versus advanatageous recruitment) and offsetting behaviour for varying quality airbags and braking systems.

Keywords: Value of research, externalities.

1 Introduction

There has been substantial empirical research on the effect that improved safety devices, such as seatbelts and airbags, have on driving behaviour and resulting accident rates (e.g., see Peltzman, 1975 and Harless and Hoffer, 2003). If the adoption of a safety device reduces the size of loss of an accident to individuals, then the marginal value of exerting effort to avoid accidents falls and one expects some reduction in safe driving behaviour which in turn increases the risk of an accident to others. This type of reaction has been termed the offsetting or risk compensation effect and should be taken into account when valuing improved safety devices or measures (see Gossner and Picard, 2005). In the case of voluntary purchase of such devices, the presence of any externality due to the offsetting effect is also a relevant policy concern (see Hoy and Polborn, 2015). The optimal intervention depends on the extent to which adoption of the safety device reduces the level of care that individuals take as well as the strength of the resulting externality effect. In a setting with heterogeneous preferences, one cannot draw clear conclusions about the strength of any offsetting behaviour created by voluntary adoption of an improved safety technology by simply comparing accident rates or driving records of adopters to non-adopters. The reason is that one needs to decompose this difference into a selection (or recruitment) effect and a behavioural effect. It is this feature of safety technologies that we investigate here.

In a classic paper, Peltzman (1975) identified an important offsetting effect due to mandatory seat belt legislation. Many empirical papers since have investigated the existence and strength of offsetting behaviour across a wide range of technologies and environments. The finding that intended improvements to safety from such regulation may be reduced, entirely eliminated, or even reversed due to offsetting behaviour is an important policy consideration. A plethora of recent developments of safety technologies,[1] which are available for voluntary purchase with select automobiles, makes further study of their effects on driving behaviour important. An important policy concern is determining whether individuals should be allowed to make their own decisions about which vehicle safety features to adopt and, if so, what role can taxes an subsidies play to improve welfare.

We develop a theoretical model with two key features which allows us to organize how to investigate the empirical effects of improved safety technologies with an eye towards providing input for policy. Firstly, assuming no change in driving behaviour, we classify technologies based on whether they have an effect on the size of loss should an accident

[1] The estimated fitment rate for recently developed safety features for 2017 global passenger vehicle production includes 14% with automated emergency braking, 8% with lane keeping assist, 11% with blind spot monitoring, and 7% with adaptive cruise control (IHS Markit - quoted in CARANDDRIVER, Nov, 2017, p. 82).

occur or, alternatively, an effect on the likelihood of incurring an accident. Safety devices such as airbags affect the size of loss due to an accident while others, such as lane departure warning systems or improved braking systems, presumably reduce the probability of an accident. We refer to these types of safety technologies as loss mitigation (LMT) and probability reduction (PRT) technologies, respectively.[2] Secondly, it is important to be able to understand the forces (individual preferences) that motivate some vehicle owners to adopt improved safety techologies and how adoption affects their driving behaviour. To this end, we assume individuals may differ either by their (subjective) size of loss should an accident occur or by their preceived cost of own effort (diligence in safe driving habits). There are, of course, many other potential behavioural traits that may influence such choices. We discuss some of these later in the paper.

One important consideration is that, depending on the extent of any possible offsetting effect, a PRT may provide for either a positive or negative externality. As long as any reduced level of attentiveness to safe driving does not completely neutralize or reverse the inherent effect of the reduced probability of a vehicle with improved PRT causing an accident, the technology provides a positive externality and so a subsidy is in order. If the adopter reduces his own efforts at safe driving so much that he becomes more likely to cause an accident, then the adoption of the PRT leads to a negative externality and should be taxed. As in the classic case of a mandated LMT (e.g., safety belts), adoption of any LMT in our model also leads to a reduction of safe driving efforts. Thus, adopters of improved LMTs generate a negative externality due to the expected offsetting effect and so a tax is in order.[3]

Compared to measuring the effects of safty innovations when they are mandatory (e.g., seat belt laws) or publicly provided (e.g., improved road barriers), there are more complications in an environment of voluntary purchase/adoption. Many questions are raised which require a careful analysis of data in any empirical exercise. What type of individuals will purchase these devices? A priori to adoption decisions, will those at higher risk of accident or lower risk of accident adopt improved safety devices? Conditional on no offsetting effects, would adopters (ex post) display higher or lower accident rates; that is, will there be adverse or advantageous recruitment in addition to possible offsetting effects? How will adoption affect driving habits in regards to safety given different reasons for choosing a particular type of safety device? Given the relevant externalities associated with offsetting behaviour, valuing such technologies requires separating the selection (recruitment) effects from behavioural effects from adoption. For example, if there is a positive correla-

[2] Some technologies may affect both the size and probability of loss, although we do not model such a mixed possibility here.

[3] See Hoy and Polborn (2015) for analysis of optimal taxation of safety technologies for both LMTs and PRTs in a setting with homogeneous individuals.

tion between adoption and accident rates but this is due entirely to selection effects and not behavioural effects, then one will draw a different conclusion about the value of such devices than if the positive correlation is due in part to some offsetting behaviour. These complications are absent when all drivers adopt the safety measure either actively through mandates or passively through public provision.

In order to generate useful intution on these matters, we consider an increasingly complex environment of safety technology adoption: Firstly, we consider mandatory adoption of technologies; second, we consider voluntary adoption of a single type of technology (e.g., LMT) while holding the level of the other technology (e.g., PRT) fixed; third, we consider the voluntary and simultaneous adoption of both types of safety technology. Each of these three settings relate well to different policy environments as discussed later in the paper. Although we do not propose explicit policy recommendations, our results point to appropriate tax/subsidy policies that would enhance welfare.

These three scenarios represent alternative polic environments regarding regulations about vehicle safety. There are many instances of specific safety features being made mandatory, such as seat belts, minimal quality airbag requirements, rear view cameras, etc.. Of particular note are laws passed by the EU requiring from 6 July 2022 that all new pasenger vehicles be fitted with a suite of features including reversing detection with camera or sensors, attention warining in case of driver drowsiness, lane keeping assist and also, between 2024 and 2025, a plan to include advanced driver distraction warning (see https://ec.europa.eu/docsroom/documents/50774). The first scenario of exogenous improvements applies to these instances. Given existing types of echnologies which are mandated, it is useful to know how those affect the value of other newly developed technologies that individuals may choose to adopt voluntarily. This is the second scenario in which we analyze introducing one or the other new PRT or LMT technology. Finally, our third scenario considers the choice problem for both types of technology offered simultaneously.

Although we do not develop specific policy conclusions, our work points in some useful directions by identifying various possible externalities from voluntary (or mandatory) adoption. We address some of these in the discussion section of the paper.

We provide an empirical application using a data set acquired from the Taiwan Insurance Institute (TII). This data set provides detailed information on insureds' claims and driving records. This data is supplemented with information from vehicle records regarding various vehicle characteristics including two safety technologies: quality of airbag systems and quality of braking systems. We designate as a high quality airbag system any vehicle with airbags equipped for both front and back seats, while we designate as a high quality braking system any vehicle which is equipped not only with an anti-lock brake system, which is standard for virtually all cars in our sample, but is also equipped with a traction control system, vehicle stability control system, acceleration slip regulation as well as down-hill assist control, and hill-start assist control. We treat the high quality airbag system as a LMT and the high quality braking system as a PRT.[4] We also consider choice of a SUV as an enhanced LMT since, in comparison to a sedan, a SUV is larger and heavier and so provides better protection to its occupants.

The data covers two years (2011 and 2012) and contains 2,371,730 observations. It is an unbalanced panel. We perform two empirical exercises. Firstly, we treat the data in a cross-sectional manner to estimate the relationship between claims arising from third party losses and various vehicle and driver characteristics including quality of braking and airbag systems. These results should be treated as descriptive of the relationship between safety technologies and accident claims since recruitment effects are not separated from behavioural effects. Second, we extract observations from the data set for those individuals who are present in both years and have an identifiable change in automobile. For these individuals we can determine if they have purchased a new (different) vehicle with higher, lower, or same quality of both airbag system (LMT) and braking system (PRT). This allows us to estimate behavioural effects of the adopted technologies without the confounding implications of possible recruitment effects.

Our propositions lead to implications on whether positive or negative correlations between adopters of a safety technology are consistent with the presence of heterogeneous cost or loss size types in the population (i.e., the presence of adverse or advantageous recruitment). There are, however, substantial challenges in drawing conclusions about actual choices of vehicle safety technologies based on such preferences. Vehicle choice is not solely driven by safety technology present in the chosen vehicle but other features of the vehicle as well which may be bundled together with safety technologies. In the case of purchasing a SUV, it seems appropriate to view the choice to be based on both safety considerations (bigger is safer) and other features (bigger means more storage space).

The paper is structured as follows. A brief literature review follows. Section 3 of this paper provides the basic theoretical model and propositions relating choice of technology to individuals based on each type of heterogeneity (i.e., differing costs of precaution and differing subjective size of loss). Section 4 describes the data and our empirical analysis. In the final section we provide a discussion of our findings.

[4] A high quality braking system presumably also has some characteristics of a LMT since, conditional on being in a potential accident scenario, a better braking system may not allow one to avoid the accident but would reduce the speed of the impact and hence reduce the size of loss.

2 Literature Review

Much of the literature about the phenomenon of offsetting behaviour has been directed at determining empirically its size in a wide variety of economic settings. We focus here on those papers relating to traffic safety.[5] Papers most closely related to ours include Harless and Hoffer (2003), who investigate the recruitment and offsetting effects of voluntary adoption of airbags and Winston, et al. (2006) who consider both adoption of airbags and antilock braking systems as do we.

In comparison to the vast range and depth of empirical research on the offsetting hypothesis, there is relatively little theoretical analysis of the phenomenon. Our model should be thought of as futher developing this stream of research. Of particular relevance to our work is the paper by Blomquist (1986). He develops a general model of driver safety behaviour and demonstrates the result that "under plausible conditions a change in exogenous safety, which is beyond driver control, causes a compensatory change in driver effort in the opposite direction", (Blomquist, 1986, p. 371). His model has both dimensions of safety as does ours (i.e., safety technologies and endogenous driver safey choice) and provides a useful comparative static result describing conditions under which the choice of exogenous safety may reduce the driver's own effort to avoid bad outcomes. However, he does not explicity model the two types of technology that we do and he also does not address welfare implications.

Neill (1993) also develops a model to determine conditions under which the probability of an accident increases or decreases as a result of an increase in the level of an imposed safety technology or regulation. As in our model, this depends on how the increase in the imposed safety technology affects the marginal benefit of individuals' own levels of precaution. His paper investigates how this relationship between the safety technology and the individual's effort to avoid accidents impact on the choice of self-insurance (LMT in our terminology and safety devices in his). However, he does not address the normative implications of imposed safety technologies and restricts his attention to $LMTs$.

Hause (2006) also develops a general model of the offsetting phenomenon. He points out (pp. 689-690) that "Despite accumulating evidence on the empirical relevance of OB (offsetting behaviour), none of the theoretical literature has provided a model determining formal conditions under which dominant or partial OB occurs, much less the magnitude of the OB effect on expected accident loss". By a dominant effect Hause means that the OB effect (change in own effort of accident avoidance) results in no net change in the expected accident loss. By a partial OB effect is meant that the net effect of the safety regulation or technology is a reduction in the net expected accident loss, but less than the

[5] For example, workplace safety (e.g., Lanoie (1992)), sports (e.g., Potter (2011) on formula 1 racing and McCannon (2011) on basketball), food safety (e.g., Miljkovic (2011), et al.).

direct effect.

Another paper that has some of the same properties and objectives as our paper is that of Gossner and Picard (2005). Their goal is to investigate how to value the benefit of an improvement in road safety in the presence of an offsetting effect. The loss in their model is financial and the source of externalities is through the insurance market They consider a similar problem as in our paper by taking into account how changes in road safety affect precautionary effort levels of individuals. Due ot the fact that losses are financial, they, also investigate the implications of drivers'risk aversion on the value of improvements to road safety. In our model, our "uninsured losses" are meant to cover uncompensated pain and suffering as well as uninsured financial losses.

The most important advantage of our model is that we combine the elements of an explicit treatment of (1) optimal choice of safety features including consideration of whether specific features (for a PRT) are strategic complements or substitutes, (2) how the safety technology affects the marginal value of precaution, and (3) whether the adopted safety technology is an LMT (mitigates loss) or a PRT (reduces probability of loss). Importantly, we allow for heterogeneity of preferences in our model in one of two dimensions (cost of driving more safely and size of loss due to an accident). These features allow us to consider most carefully the interplay between adoption decisons (recruitment) and offsetting behaviour.

3 Models

In this section we first develop the individual's objective function based on the level of each type of technology (PRT and LMT) and two possible types of preference heterogeneity. We allow for individuals to differ either by size of loss amount due to an accident as well as differeing cost of precaution. As noted earlier in the paper, we develop our model in the context of three regulatory environments. The first involves describing the effect of an exogenous increase to one or the other type of technology while in the second we treat the case where the individual chooses a level of each type of technology while holding the level of the other technology fixed. Finally, we allow for simultaneous choice of levels of PRT and LMT.

We analyze separately each scenario for individuals who differ due to heterogeneous cost of precaution and due to heterogeneous perception of size of loss. In regards to generating the possibilities of advantageous versus adverse recruitment, the source of heterogeneity is crucial. The implications for analyzing the relationship between levels of these safety technologies and driving behaviour in the data are, of course, complicated by the effects of offsetting behaviour.

We assume each individual chooses (or required to adopt) a level of PRT, θ, and LMT, λ. For a given level of own care, p, a higher level of θ reduces the probability of an accident while a higher level of λ reduces the size of loss should an accident occur. Although some safety technologies no doubt have both effects, we do not model such a possibility.[6]

The probability of an accident (claim) is $D(p, \theta) \in (0, 1)$ with partial derivatives D_p, $D_\theta < 0$, D_{pp}, $D_{\theta\theta} > 0$. Given that a lower value of D_p (resp. D_θ) means p (resp. θ) is at the margin more productive in reducing the probability of an accident, it follows that $D_{p\theta} > 0$ implies that a higher value of θ reduces the marginal productivity of p or, equivalently, a lower value of θ increases the marginal productivity of p (and vice versa). In this case we say that own care and the PRT are substitutes. It seems plausible that a technology like lane departure warning would be a substitute for own care as it could give confidence to drive while more tired and/or pay less attention to one's location on the road. Therefore, if one person has a higher cost of own care then we might expect such a person to acquire a higher level of PRT when it is a substitute for own care (i.e., when $D_{p\theta} > 0$). It seems at least possible that choosing a higher quality ABS system, which is one of the variables of interest in our data set, may improve effectiveness of own care since more dangerous situations can be avoided if one is both more alert and has better brakes - an example of complementarity (i.e., $D_{p\theta} < 0$). On the other hand, it is also possible that better brakes reduces the benefit of driving at modest speeds since the braking distance to a stationary (or slower) vehicle is less and so collisions can be avoided at higher speeds. The sign of this cross-partial not surprisingly is important and so we investigate both possibilities. It seems intuitively appealing that if $D_{p\theta} < 0$, then purchasing a higher level of PRT may actually have a reverse offsetting effect (i.e., lead to an increase in own care and so a reinforcement of the reduction in loss probability). We also assume $D(p, \theta)$ is a strictly convex function.

We also acknowledge here, but do not explicitly model, that the level of care of other drivers will have an effect on an individual's probability of an accident and also may well affect the marginal benefit of both the individual's level of precaution (D_p) and PRT (D_θ). This is explicitly taken into account for a much simpler model with homogeneous individuals and only one type of safety technology in Hoy and Polborn (2015). In that paper, the equilibrium level of choice variables is the same as each individual's optimal value. With heterogeneous preferences, each individual generally chooses a different level for all variables and so equilibrium analysis and formal comparative statics analysis becomes unmanageable. We do, however, return to this issue when addressing our empirical

[6] An improved braking system seems a good candidate for possessing both effects. Being able to brake in a shorter distance (and in a more controled manner) should reduce the probability of being involved in an accident and, conditional on being involved in an accident, may well reduce the consequences.

strategy.

The size of the loss is $L(\lambda) \geq 0$ and depends on the level of LMT (λ) with $L_\lambda < 0$. We assume $L_{\lambda\lambda} < 0$. The loss is not meant to be a financial loss but is measured in monetary equivalent utility terms.[7] Similarly, we let the cost of own care be measured in monetary equivalent terms and represented by $c(p)$ with $c', c'' > 0$. The financial cost of PRT and LMT levels are represented by $k_R(\theta)$ and $k_M(\lambda)$ with both being increasing and strictly convex functions. Each individual chooses $\{p, \lambda, \theta\}$ to minimize

$$\Omega(p, \lambda, \theta) = D(p, \theta)L(\lambda) + c(p) + k_R(\theta) + k_M(\lambda) \tag{1}$$

In the scenario in which differential costs of precaution is the source of individual heterogeneity, we replace $c(p)$ with $(1 + \tau)c(p)$, $\tau \geq 0$ where higher τ represents an individual having higher cost of precaution. In the scenario in which individual heterogeneity is the result of differential size of loss, we replace $L(\lambda)$ with $(1 + \nu)L(\lambda)$, $\upsilon \geq 0$ where higher ν represents an individual having a higher loss from an accident.[8]

We do not include in our objective function characteristics of risk preferences beyond the subjective parameter which can reflect either differences in (subjective) size of loss or a weighting parameter on the probability of loss. In the context of our data, the set of insurance contracts available to consumers is tightly regulated by the Taiwan Insurance Institute and so we believe risk preferences over financial losses resulting from accidents is not an important factor to model. For other settings/countries, this would not be a reasonable assumption and alterations to the objective function which account for alternative risk preferences over financial outcomes would be important to include.

In each model, our reference to expected losses includes whatever costs are pertinent to the individual's choice problem (i.e., the cost of precaution for all models and also the cost of the PRT and LMT when those are purchased voluntarily. We first present the models for exogenous changes in levels θ, λ.

3.1 Exogenous changes to PRT and LMT

Governments often introduce mandatory use of safety equipment (e.g., helmets, safety belts, airbags, rear cameras, winter tires, etc.) or make safety improvements to roads (e.g., rumble strips, crash barriers, illuminated lines, lighting, etc.). To represent the effects of such policies, we write θ and λ as exogenously set at values $\overline{\theta}$ and $\overline{\lambda}$, respectively, and note that individuals incur no (direct) cost to these changes. We first consider case in which the source of heterogeneity is due to a differential cost of precaution. Therefore,

[7] See Hoy and Polborn (2015) for discussion.

[8] We assume these are uninsurable losses of accident victims. A good discussion of what these may can be found in Gossner and Picard (2005). We discuss a potential role for insurance later in this paper.

we assume an individual chooses precaution, p, to minimize the expected loss Ω where:

$$\Omega(p, \overline{\lambda}, \overline{\theta}) = D(p, \overline{\theta})L(\overline{\lambda}) + (1+\tau)c(p) \tag{2}$$

and refer to this scenario as Model A1.

The first order condition is

$$F_p(p, \overline{\lambda}, \overline{\theta}) = D_p L + (1+\tau)c' = 0 \tag{3}$$

Upon totally differentiating with respect to p and $\overline{\theta}$, we obtain:

$$\frac{dp}{d\overline{\theta}} = -\frac{D_{p\theta}L}{[D_{pp}L + (1+\tau)c'']} \tag{4}$$

Given that the denominator is positive (i.e., both D_{pp} and c'' are positive), it follows that the sign of $\frac{dp}{d\overline{\theta}}$ is the same as the sign of $D_{p\theta}$. This is intuitively pleasing since if own care and the level of the PRT are substitutes ($D_{p\theta} > 0$) then one would expect an increase in θ would lead to a reduction in p and vice versa if they are complements.

We can follow the same procedure to determine the effect of an exogenous change in the level of LMT ($\overline{\lambda}$) on own care. We obtain:

$$\frac{dp}{d\overline{\lambda}} = -\frac{D_p L_\lambda}{[D_{pp}L + (1+\tau)c'']} < 0 \tag{5}$$

The above represents a classic offsetting effect (e.g., Peltzman, 1975); that is, a reduction in the size of loss due to an exogenous policy intervention like mandatory seatbelts leads to a reduction in own care.

It is also interesting to see how, given exogenous levels of PRT and LRT, individual care varies according to the level of an individual's extra cost of care, τ. It is straightforward to show upon totally differentiating (3) with respect to p and τ, one obtains

$$\frac{dp}{d\tau} = -\frac{c'}{[D_{pp}L + (1+\tau)c'']} < 0 \tag{6}$$

This is intuitively pleasing since one would expect those with higher cost of precaution would engage in less precaution.

Proposition 1. *Suppose individuals differ according to cost of precaution. At given levels of PRT and LMT, individuals with higher cost of precaution choose a lower level of precaution. An exogenous increase in the level of PRT technology leads to a reduction (increase) in precaution if the PRT is a substitute (complement) to precaution. An exogenous increase in the level of LMT will lead to a reduction in the chosen level of precaution.*

Consider the case in which the source of heterogeneity is due to a differential size of loss, should an accident occur. The individual chooses precaution, p, to minimize the expected loss Ω where:

$$\Omega(p, \overline{\lambda}, \overline{\theta}) = D(p, \overline{\theta})[(1+\nu)L(\overline{\lambda})] + c(p) \tag{7}$$

and refer to this scenario as Model A2.

The first order condition is

$$F_p(p, \overline{\lambda}, \overline{\theta}) = D_p(1+\nu)L + c' = 0 \tag{8}$$

Upon totally differentiating with respect to p and $\overline{\theta}$, we obtain:

$$\frac{dp}{d\overline{\theta}} = -\frac{D_{p\theta}(1+\nu)L}{[D_{pp}(1+\upsilon)L + c'']} \tag{9}$$

As in the case for heterogeneity due to differential cost of precaution, the sign of $\frac{dp}{d\overline{\theta}}$ is the same as the sign of $D_{p\theta}$.

We can follow the same procedure to determine the effect of an exogenous change in the level of LMT $(\overline{\lambda})$ on own care. We obtain:

$$\frac{dp}{d\overline{\lambda}} = -\frac{D_p(1+\lambda)L_\lambda}{[D_{pp}(1+\upsilon)L + c'']} < 0 \tag{10}$$

which represents a classic offsetting effect (e.g., Peltzman, 1975).

It is also interesting to see how, given exogenous levels of PRT and LMT, individual care varies according to the level of an individual's extra loss from an accident, ν. It is straightforward to show upon totally differentiating (8) with respect to p and ν, one obtains

$$\frac{dp}{d\nu} = -\frac{D_pL(\overline{\lambda})}{[D_{pp}L + (1+\tau)c'']} > 0 \tag{11}$$

and so, as one would expect, those with higher loss from an accident engage in more precaution. We summarize these results in the following proposition.

Proposition 2. *Suppose individuals differ according to the size of loss due to an accident. At given levels of PRT and LMT, individuals with higher loss choose a higher level of precaution. An exogenous increase in the level of PRT technology leads to a reduction (increase) in precaution if the PRT is a substitute (complement) to precaution. An exogenous increase in the level of LMT will lead to a reduction in the chosen level of precaution.*

We see that if levels of PRT and LMT are determined exogenously, whether heterogeneity is due to differential cost of precaution or differential size of loss due to accident, the effect of an increase in PRT is to lead to an reduction (increase) in precaution if the PRT and precaution are substitutes (complements). The effects of heterogeneity on levels of precaution for any given (exogenously fixed) levels of PRT and LMT are as expected: higher cost individuals choose lower levels of precaution while higher loss individuals choose higher levels of precaution. Comparing levels of precaution across heterogeneous types is less straightforward when all variables are endogenously determined (i.e., chosen at a financial cost by individuals). Moreover, comparing the resulting loss probabilities (accident rates) across heterogeneous individuals is also straight forward: higher cost individuals experience higher accident rates while higher loss individuals experience lower accident rates. As we show below, such comparisons are not so straightforward when individuals choose levels of PRT and LMT. Selection effects combined with behavioural (offsetting) effects lead to a more complicated determination of such comparisons.

3.2 Endogenous Choice of one of PRT or LMT

We now return to the main concern of this paper which is the endogenous choice of safety technologies. In order to better develop intuition, it is helpful to begin with the restriction that each individual chooses a level of safety technology of only one type with the other type set at a fixed level. First we explore the scenario in which individuals differ according to cost of precaution and are faced with a fixed value of PRT ($\theta = \overline{\theta}$) and choose $\{p, \lambda\}$ to maximize:

$$\Omega(p, \lambda, \overline{\theta}) = D(p, \overline{\theta})L(\lambda) + (1+\tau)c(p) + k_R(\overline{\theta}) + k_M(\lambda) \tag{12}$$

Note the change in order of variables with $p \longrightarrow 1$, $\lambda \rightarrow 2$, and $\tau \longrightarrow 3$. This leads to first-order conditions:

$$F_1(p, \lambda, \overline{\theta}) = D_p(p, \overline{\theta})L(\lambda) + (1+\tau)c'(p) = 0 \tag{13}$$

$$F_2(p, \lambda, \overline{\theta}) = D(p, \overline{\theta})L_\lambda(\lambda) + k'_M(\lambda) = 0 \tag{14}$$

Total differentiation gives:

$$dF_1 = F_{11}dp + F_{12}d\lambda + F_{13}d\tau = 0 \tag{15}$$

$$dF_2 = F_{21}dp + F_{22}d\lambda + F_{23}d\tau = 0 \tag{16}$$

where $F_{11} = D_{pp}L + (1+\tau)c'' > 0$, $F_{12} = F_{21} = D_pL_\lambda > 0$, $F_{22} = DL_{\lambda\lambda} + k''_M > 0$, $F_{13} = c'$, $F_{23} = 0$. Thus, with $\mid F \mid > 0$, we have

$$\begin{bmatrix} F_{11} & F_{12} \\ F_{21} & F_{22} \end{bmatrix} \begin{bmatrix} dp/d\tau \\ d\lambda/d\tau \end{bmatrix} = \begin{bmatrix} -F_{13} \\ -F_{23} \end{bmatrix} = \begin{bmatrix} -c'(p) \\ 0 \end{bmatrix} \tag{17}$$

which gives (reasons stated below):

$$\frac{dp}{d\tau} = \frac{\begin{vmatrix} -c'(p) & F_{12} \\ 0 & F_{22} \end{vmatrix}}{\mid F \mid} = \frac{-c'(p)F_{22}}{\mid F \mid} < 0 \tag{18}$$

$$\frac{d\lambda}{d\tau} = \frac{\begin{vmatrix} F_{11} & -c'(p) \\ F_{21} & 0 \end{vmatrix}}{\mid F \mid} = \frac{c'(p)F_{21}}{\mid F \mid} > 0 \tag{19}$$

The higher cost types choose a lower level of precaution which, since that effect increases the marginal productivity of the LMT (λ), leads to them choosing a higher level of λ.

Consider the same scenario except for the situation in which individuals differ due to size of loss parameter υ. Individuals choose $\{p, \lambda\}$ to maximize:

$$\Omega(p, \lambda, \overline{\theta}) = D(p, \overline{\theta})(1 + \upsilon)L(\lambda) + c(p) + k_R(\overline{\theta}) + k_M(\lambda) \tag{20}$$

This leads to first-order conditions:

$$F_1(p, \lambda; \upsilon) = D_p(p, \overline{\theta})(1 + \upsilon)L(\lambda) + c'(p) = 0 \tag{21}$$

$$F_2(p, \lambda; \upsilon) = D(p, \overline{\theta})(1 + \upsilon)L_\lambda(\lambda) + k'_M(\lambda) = 0 \tag{22}$$

Total differentiation gives:

$$dF_1 = F_{11}dp + F_{12}d\lambda + F_{13}d\upsilon = 0 \tag{23}$$

$$dF_2 = F_{21}dp + F_{22}d\lambda + F_{23}d\upsilon = 0 \tag{24}$$

where $F_{11} = D_{pp}(1+\upsilon)L + c'' > 0$, $F_{12} = F_{21} = D_p(1+\upsilon)L_\lambda > 0$, $F_{22} = D(1+\upsilon)L_{\lambda\lambda} + k''_M > 0$, $F_{13} = D_pL < 0$, $F_{23} = DL_\lambda < 0$.

Thus, with $\mid F \mid > 0$, we have

$$\begin{bmatrix} F_{11} & F_{12} \\ F_{21} & F_{22} \end{bmatrix} \begin{bmatrix} dp/d\upsilon \\ d\lambda/d\nu \end{bmatrix} = \begin{bmatrix} -F_{13} \\ -F_{23} \end{bmatrix} = \begin{bmatrix} -D_pL \\ -DL_\lambda \end{bmatrix} \tag{25}$$

which gives (reasons stated below):

$$\frac{dp}{d\nu} = \frac{\begin{vmatrix} -D_pL & F_{12} \\ -DL_\lambda & F_{22} \end{vmatrix}}{\mid F \mid} = \frac{-D_pLF_{22} + DL_\lambda F_{12}}{\mid F \mid} \tag{26}$$

$$\frac{d\lambda}{d\upsilon} = \frac{\begin{vmatrix} F_{11} & -D_pL \\ F_{21} & -DL_\lambda \end{vmatrix}}{\mid F \mid} = \frac{-DLF_{11} + D_pLF_{12}}{\mid F \mid} \tag{27}$$

In both equations above, the first term of the numerator is positive but the second is negative. Therefore, neither has a definitive sign. A higher value of υ leads to an increase in the marginal productivity of both the LMT (λ) and precaution (p). It may then be the case, for example, that an individual with higher υ will find it worthwhile to choose a sufficiently higher value of λ so as to lower the size of loss of life enough that the marginal productivity of precaution falls.

We refer to these as Models B1.i and B2.i and we summarize the results in the following two pairs of equations with associated propositions.

Model B1.i: Individuals differ according to the cost of precaution and face a fixed level of PRT. Higher cost individuals choose a lower level of precaution and a higher level of LMT and, on average, experience both a higher accident rate and worse driving record.

$$\frac{dp}{d\tau} = \frac{-c'(p)F_{22}}{\mid F \mid} < 0, \quad \frac{d\lambda}{d\tau} = \frac{c'(p)F_{21}}{\mid F \mid} > 0 \tag{28}$$

Proposition 3. *Suppose individuals differ according to cost of precaution, the level of available PRT is fixed, and individuals choose level of precaution and LMT to minimize expected loss. Individuals with higher cost of precaution choose a lower level of precaution and a higher level of LMT and, on average, experience both a higher accident rate and worse driving record.*

Model B2.i: Individuals differ according to the size of loss and face a fixed level of PRT. The net effects on their levels of precaution and LMT are ambiguous. Although marginal productivity of each choice variable is higher for higher loss individuals, responding with a higher choice of one of the variables may lead to a reduction in the optimal choice of the other variable. Therefore, we cannot predict whether higher loss individuals will, on average, experience a lower or higher accident rate or a better or worse driving record.

$$\frac{dp}{d\nu} = \frac{-D_pLF_{22} + DL_\lambda F_{12}}{\mid F \mid}, \quad \frac{d\lambda}{d\upsilon} = \frac{-DLF_{11} + D_pLF_{12}}{\mid F \mid} \tag{29}$$

Proposition 4. *Suppose individuals differ according to size of loss, the level of available PRT is fixed, and individuals choose level of precaution and LMT to minimize expected loss. The relationships between the size of loss and any of the other variables of interest (i.e., level of precaution, level of LMT, average driving record or accident rate) are indeterminate.*

We now explore the scenario in which individuals differ according to cost of precaution and are faced with a fixed value of LMT ($\lambda = \overline{\lambda}$) and choose $\{p, \theta\}$ to maximize:

$$\Omega(p, \theta, \overline{\lambda}) = D(p, \theta)L(\overline{\lambda}) + (1 + \tau)c(p) + k_R(\theta) + k_M(\overline{\lambda}) \tag{30}$$

Note the change in order of variables with $p \longrightarrow 1$, $\theta \rightarrow 2$, and $\tau \longrightarrow 3$. The first-order conditions are:

$$F_1(p, \theta, \overline{\lambda}) = D_p(p, \theta)L(\overline{\lambda}) + (1 + \tau)c'(p) = 0 \tag{31}$$

$$F_2(p, \theta, \overline{\lambda}) = D_\theta(p, \theta)L(\overline{\lambda}) + k'_R(\theta) = 0 \tag{32}$$

Total differentiation gives:

$$dF_1 = F_{11}dp + F_{12}d\theta + F_{13}d\tau = 0 \tag{33}$$

$$dF_2 = F_{21}dp + F_{22}d\theta + F_{23}d\tau = 0 \tag{34}$$

where $F_{11} = D_{pp}L + (1+\tau)c'' > 0$, $F_{12} = F_{21} = D_{p\theta}L$ (sign of $D_{p\theta}$), $F_{22} = D_{\theta\theta}L + k_R'' > 0$, $F_{13} = c'$, $F_{23} = 0$. Thus, with $\mid F \mid > 0$, we have

$$\begin{bmatrix} F_{11} & F_{12} \\ F_{21} & F_{22} \end{bmatrix} \begin{bmatrix} dp/d\tau \\ d\theta/d\tau \end{bmatrix} = \begin{bmatrix} -F_{13} \\ -F_{23} \end{bmatrix} = \begin{bmatrix} -c'(p) \\ 0 \end{bmatrix} \tag{35}$$

which gives (reasons stated below):

$$\frac{dp}{d\tau} = \frac{\begin{vmatrix} -c'(p) & F_{12} \\ 0 & F_{22} \end{vmatrix}}{\mid F \mid} = \frac{-c'(p)F_{22}}{\mid F \mid} < 0 \tag{36}$$

$$\frac{d\theta}{d\tau} = \frac{\begin{vmatrix} F_{11} & -c'(p) \\ F_{21} & 0 \end{vmatrix}}{\mid F \mid} = \frac{c'(p)D_{p\theta}L}{\mid F \mid} \begin{Bmatrix} > 0 \text{ if } D_{p\theta} > 0 \\ < 0 \text{ if } D_{p\theta} < 0 \end{Bmatrix} \tag{37}$$

The higher cost types choose a lower level of precaution and a higher (lower) level of the PRT (θ) if the PRT and precaution are substitutes (complements).

Consider the same scenario except for the situation in which individuals differ due to size of loss parameter υ. Individuals choose $\{p, \theta\}$ to maximize:

$$\Omega(p, \theta, \overline{\lambda}) = D(p, \theta)(1+\upsilon)L(\overline{\lambda}) + c(p) + k_R(\theta) + k_M(\overline{\lambda}) \tag{38}$$

Note the change in order of variables with $p \longrightarrow 1$, $\theta \to 2$, and $\upsilon \longrightarrow 3$. This leads to first-order conditions:

$$F_1(p, \theta, \overline{\lambda}) = D_p(p, \theta)(1+\upsilon)L(\overline{\lambda}) + c'(p) = 0 \tag{39}$$

$$F_2(p, \theta, \overline{\lambda}) = D_\theta(p, \overline{\theta})(1+\upsilon)L(\lambda) + k_R'(\theta) = 0 \tag{40}$$

Total differentiation gives:

$$dF_1 = F_{11}dp + F_{12}d\theta + F_{13}d\upsilon = 0 \tag{41}$$

$$dF_2 = F_{21}dp + F_{22}d\theta + F_{23}d\upsilon = 0 \tag{42}$$

where $F_{11} = D_{pp}(1+\upsilon)L + c'' > 0$, $F_{12} = F_{21} = D_{p\theta}(1+\upsilon)L$ (same sign as $D_{p\theta}$), $F_{22} = D_{\theta\theta}(1+\upsilon)L + k_R'' > 0$, $F_{13} = D_pL < 0$, $F_{23} = D_\theta L < 0$.

Thus, with $\mid F \mid > 0$, we have

$$\begin{bmatrix} F_{11} & F_{12} \\ F_{21} & F_{22} \end{bmatrix} \begin{bmatrix} dp/d\upsilon \\ d\theta/d\nu \end{bmatrix} = \begin{bmatrix} -F_{13} \\ -F_{23} \end{bmatrix} = \begin{bmatrix} -D_pL \\ -D_\theta L \end{bmatrix} \tag{43}$$

which gives (reasons stated below):

$$\frac{dp}{d\nu} = \frac{\begin{vmatrix} -D_pL & F_{12} \\ -D_\theta L & F_{22} \end{vmatrix}}{\mid F \mid} = \frac{-D_pLF_{22} + D_\theta L D_{p\theta}(1+\upsilon)L}{\mid F \mid} \tag{44}$$

$$\frac{d\theta}{d\upsilon} = \frac{\begin{vmatrix} F_{11} & -D_pL \\ F_{21} & -D_\theta L \end{vmatrix}}{\mid F \mid} = \frac{-D_\theta LF_{11} + D_p L D_{p\theta}(1+\upsilon)L}{\mid F \mid} \tag{45}$$

In both equations above, the first term of the numerator is positive. The second term is positive (negative) if precaution and the PRT are complements (substitutes). Therefore, if precaution and PRT are complements, then individuals with a higher loss choose both a higher level of precaution and the PRT. In this case, those with higher levels of the safety technology (PRT) will be observed to have a lower accident rate and an improved driving record. If the PRT and precaution are substitutes, then it is possible that the negative second term will dominate the positive first term and one of the two partial derivatives will be negative. Thus, it is possible that a higher loss type might choose a lower level of precaution and end up with a worse driving record. By simple observation of the first order condition, it is not possible that a higher loss type would choose both a lower level of precaution AND lower level of PRT since that would imply optimal choices leading to higher marginal benefit than marginal cost for both choice variables.

We refer to these two scenarios analyzed above (i.e., heterogeneous cost types and heterogeneous loss types) as Models B1.ii and B2.ii. We summarize the results with the following propositions.

Proposition 5. *Suppose individuals differ according to cost of precaution, the level of available LMT is fixed, and individuals choose level of precaution and PRT to minimize expected loss. Individuals with higher cost of precaution choose a lower level of precaution and a higher (lower) level of the PRT if precaution and the PRT are complements (substitutes). As a result, one cannot infer whether those individuals holding a higher level of the safety technology (PRT) have a higher or lower accident rate or better or worse driving record.*

Proposition 6. *Suppose individuals differ according to size of loss, the level of available LMT is fixed, and individuals choose level of precaution and PRT to minimize expected loss. Individuals with higher loss from an accident will choose both higher levels of precaution and the PRT if these are complements. In that case we would observe lower accident levels and better driving records for those who choose higher levels of the safety technology (PRT). However, if the precaution and PRT are substitutes, it is possible that individuals with higher loss from an accident will choose either a lower level of precaution or a lower* *level of PRT. Therefore, it is possible that we would observe worse driving records, but better accident records, for those who hold higher levels of the safety technology (PRT).*

The scenario in which individuals choose simultaneously their levels of precaution, PRT, and LMT, comparative static results mirroring those in the above propositions are more complex mathematically and do not generate any definitive derivative signs of interest. Although the above analysis helps in understanding the intuition for the outcomes when choice variables are made simultaneously, one must rely on empirical analysis to draw any conclusions about changes in offsetting effects due to improved technologies for PRT and LMT becoming available. Therefore, we relegate the exercise of comparative statics determination to the appendix and move on to the empirical analysis in the following section.

4 Empirical Application

In this section, we examine our theoretical predictions by adopting a detailed individual level data of almost all passenger automobile liability insurance contracts sold in Taiwan during 2011 and 2012. To maintain the homogeneity in the incentive on the demand in safety equipment and the purpose of using the vehicles as much as is possible, only private passenger vehicles are included. Our data comprises safety information of the insured vehicles, the characteristics of the policyholders and the insurance experiences, including claims experiences and bonus-malus adjustment. With this unique and complete data, we can empirically investigate the relationship between the adoption in safety technology and the accident rate.

It is important to note that the source of the negative externality in our problem differs from the adverse selection problem in insurance. In that model, the externality arises due to the insurer not being able to identify the risk level of consumers and so high risk types can mimic low risk types which generates a negative externality which typically involves low risk types receiving too little insurance coverage. In our problem, the externality from offsetting behaviour associated with the voluntary adoption of safety technologies arises whether the perpretrators' identities are known or not. Of course, if behaviour were observable, some agent (e.g., the government) could intervene in an effective way to improve welfare.[9]

[9] Our paper follows closely the methodology in Hoy and Polborn (2015) which is essentially an application of the phenomenon of moral hazard in teams. See Holmstrom (1982) for a general characterization of this problem and Cooper and Ross (1985), Lanoie (1991), Pedersen (2003), and Risa (1992, 1995) for useful applications.

4.1 Data

Our data is acquired from Taiwan Insurance Institute (TII), which is a data and research platform of the insurance industry governed by the Financial Supervisory Commission in Taiwan. The TII data includes the type of insurance contracts, claims made, the characteristics of the policyholders and the insured vehicles but the safety information of the vehicles is absent. Thus, by matching the vehicle type, brand, model, and year of manufacture recorded in the TII data, we hand collect the information regarding the safety technology for each insured private passenger automobile via auto magazines, auto manufacture reports and the web sites of all possible resources. To reduce the burden of data collection, we focus on the top four vehicle brands in Taiwan, which accounts for more than 80% of the market share. In total, we have 2,371,730 observations during the data period 2011 to 2012. We are able to link some individuals present in the two years as described below.

For the first part of the empirical analysis we use the complete set of observations. For the second part of our empirical analysis, we extract only those observations based on individuals present in the data set for both years and with relevant information available. There are 1,786,490 observations from 893,245 individuals who are in both years of the data. Thus, we lose 2,371,730 − 1,786,490 = 585,240 observations. Some of the excluded individuals were insured in only one of the years 2011 and 2012. Of the 893,245 individuals who we can track and identify whether they replace their vehicle, there are 17,002 owners who purchased a new (or rather different) vehicle in 2012 and chose the same insurance company as in 2011. For this group, we can determine whether they switched to a vehicle with higher or lower or same quality of airbag and brake system.

Taken at face value, these numbers imply an unreasonably low fraction of individuals purchasing a new vehicle in a given year of 1.9% (i.e. 17,002/893,245 = 0.019). On average, about 8% of vehicle owners purchase a new car each year. The reason for this discrepancy is that an over-represented set of individuals who make up the 585,240 excluded observations purchased new cars at a disproportionately higher rate but have been excluded because we cannot track the specific change in vehicle characteristics. Consistency implies that approximately 20% (118,386) out of the 585,240 excluded observations purchased a new car but the information is lost as they switched insurers; i.e., (17,002 + 59,193)/(893,245 + 59,193) = 0.08.[10]

We use the claim on compulsory liability insurance as a proxy for traffic accidents .

[10] In Taiwan, when people purchase a new car, the car dealer will "recommend" an insurance company to the new car owner. Many car owners take up this recommendation. As a result, we lose the information on these new car owners if they purchased the new car and accepted the recommendation to the target insurance company in year 2012.

Compulsory liability insurance is designed to provide basic coverage for the third party's life as well as bodily injury caused by the usage of vehicles.[11] Every vehicle must be insured with this type of insurance and so our data set is comprehensive. In addition, we only included accidents involving a third party. Therefore, problems involving unclaimed accidents, a common feature of this data, are irrelevant to our study. Occupants of cars with airbags will presumably less frequently suffer bodily injury or death when involved with an accident. Including them would create a bias (see Harless and Hoffer (2003) for a discussion of this issue which contaminates their data set). It is an advantage that we can include only those accidents that involve a third party since the added protection of a LMT on any car that causes the accident would create a bias. However, a vehicle which triggers a third party claim creates no problem of bias based on whether it has a higher quality airbag. To compensate in the event of insufficient coverage under compulsory insurance, individuals can further purchase voluntary third party bodily injury or property damage liability insurance, which respectively covers bodily injury or property damage sustained by the third party.

Individuals with a higher degree of risk aversion may demand more insurance. Therefore, we divide our sample into two subsamples: one includes observations covered by voluntary third party bodily injury liability insurance (about 57%), and the other includes those without this type of additional insurance coverage (about 43% possess only compulsory third party insurance). Note that the risk covered in voluntary third party property damage liability insurance is different from the risk covered by compulsory liability insurance. Thus, we do not divide our sample according to the decision on the choice of voluntary third party property damage liability insurance.

As for many other countries, Taiwan has a bonus-malus system to provide an incentive for careful driving. The bonus malus coefficients in compulsory insurance could be 0.7, 0.74, 0.82, 1, 1.1, 1.2, 1.3, 1.4, 1.5, and 1.6. New drivers start at 1. If they remain claim free in the current policy year, then their bonus-malus coefficient become 0.82 in the following year, which means that they will enjoy an 18% price discount. If they remain claim free, then their coefficient will fall to 0.74 in the following year. The lowest coefficient possible is 0.7, which implies a 30% price discount. If a new driver has at least one claim in the current policy year, then the coefficient becomes 1.1 in the following year. Since this variable is determined by past driving records, we treat bm as a proxy for the risk type of an individual.

Two types of safety equipment are considered: airbag and braking system. Since

[11] Under the compulsory liablility insurance, the coverage for life is NT$1,600,000. For bodily injury, the coverage depends on the degree of incapacity, ranging between NT$40,000 and NT$1,600,000. It also covers medical expenses, including the costs of first aid and treatment with an upper-limit of NT$200,000.

almost every vehicle has at least one airbag and every vehicle has at least a standard anti-lock braking system, we examine the effect of the demand for high quality airbag and braking systems on claims. The high quality airbag system means the airbag is equipped in both front and back seats, while a high quality braking system means that the vehicle is equipped not only with an anti-lock brake system, but is also equipped with traction control system, vehicle stability control system, acceleration slip regulation as well as down-hill assist control, and hill-start assist control. We view the high quality airbag system as an improved LMT, and the high quality breaking system as an improved PRT.

We also consider the choice of purchasing a SUV rather than a car. We consider two aspects of SUVs on safety. On one hand, SUVs have a size advantage and thus afford protection to the driver and passengers of the vehicle. On the other hand, SUVs are heavy vehicles, which usually have a high impact in a traffic accident. If another vehicle or a pedestrian is hit by a SUV, there is a high chance that the passengers in the hit vehicle or the pedestrian would be seriously injured. This has a positive effect on probability of a claim involving third party bodily injury or death. Thus, SUVs could be viewed as having properties of both a higher level of LMT (lower loss to its occupants should an accident occur) and a lower level of PRT in that any accident is more likely to trigger a third party claim for bodily injury or death. Our data includes information on the policyholders, such as gender, marital status, and age. Other information on the insured vehicles are also included, such as vehicle age, and the vehicle registration location. Table 1 shows the definition of all variables used in our study.

As noted above, our sample is a two-year unbalanced panel data set which covers years 2011 and 2012. Panels A, B, and C of Table 2 respectively show the basic statistics of our variables for the whole sample, the subsample that is covered by voluntary third party bodily injury insurance, and the subsample that is not covered by voluntary third party bodily injury insurance. Panel A shows that about 47% of our research sample is in year 2011. The average claim rate (claim = 1) is 1%. About 80% of the observations have been rewarded by the bonus malus system and get a 30% discount (Dbm = 0). We classify the rest 20% of the observations (Dbm = 1) as high risk type according to past driving records. For safety equipment, about 10% of the observations have a high quality airbag system (airbag_high = 1), 39% have a high quality braking systems (brake_high = 1), and 8% of are SUVs (veh_suv = 1). Panel A further shows that fewer than 1% of the vehicles are equipped with both a high quality airbag and a high quality braking systems, whereas there are 51% of the vehicles are equipped with both standard quality airbag and braking systems. Females (female = 1) account for 60% of the registered car owners. About 75% of the insured are married. Age is highly concentrated in the 30 to 60 years old group (age3060 = 1). New cars (carage0 = 1) account for about 7% of the sample, and about 61% of the cars are more than 4 years old. From Panels B and C, we see that the subsample with voluntary third party bodily injury insurance have a 28% higher claim frequency, have a (slightly) better bonus-malus score and are less likely to have high quality airbag or breaking systems. These observations are suggestive of individuals with higher insurance levels being of lower risk (i.e., advantageous selection in the insurance context). However, much more attention to this issue is required to draw any strong conclusions.

Table 3 reports the correlations between the proxies of accident risk (third party claims), driver risk type (bonus-malus score) and the safety technologies for LMT and PRT. We see that claim and Dbm are significantly positively correlated, as one would expect, implying that individuals with worse accident history (higher bonus-malus coefficient) have a higher chance to file a claim in a given year. The correlation coefficient between $claim$ and $airbag\_high$ and between Dbm and $airbag\_high$ is -0:005 and -0:004, respectively. Both of the coefficients are significant. Since the high quality airbag systems could be viewed as a LMT, this finding provides preliminary evidence for advantageous recruitment with any offsetting effect not strong enough to counter the recruitment effect. Table 3 also shows that $brake\_high$ is significantly negatively correlated with both Dbm and claim. This supports the view that high quality braking systems are purchased by more cautious drivers, which is also consistent with advantageous recruitment. Moreover, the combined effect of adopting this high quality PRT (i.e., recruitment effect net of any possible offsetting effect) is a reduction of the probability of a claim. Interestingly, the correlation between veh_suv and $claim$ is insignificant, but veh_suv is significantly positively correlated with Dbm. One possible reason for the relationship could be that individuals with a high bonus-malus coefficient (high risk drivers) purchase SUVs to protect themselves as well as any other passengers in the vehicle. However, the safety advantage of SUVs is offset by the increased risk effect from drivers of SUVs. Of course, there are many other possible explanations for all of these tentative conclusions. For example, people who purchase SUVs may be from an age group which includes individuals with different driving abilities. The following two subsections investigate these matters more thoroughly through the use of probit regression equations.

In the first of these (subsection 4.2 below), we preform a probit regression with dependent variable claims[12] for the entire data set treated as a cross-section. In the second exercise (subsection 4.3 below) we investigate the impact of changes in the quality level of airbags and braking systems on drivers' claim experience for those who purchase a new car in 2012 in order to generate a more convincing test for offsetting behaviour.

[12] Recall that claims are from accidents involving bodily injuries and deaths to third parties as covered by compulsory liability insurance.

4.2 Statistical Evidence: Part 1 - Crossectional Analysis

In this subsection we investigate the relationship between accident rates and the choice of safety technologies based on our entire sample (treated as a cross-section). Doing so provides a better understanding of the relationships between accident risk and vehicle safety technologies than simple correlations. However, the results are still descriptive in that we cannot separate recruitment and behavioural (offsetting) effects of improved LMT and PRT technologies. We may tentatively identify how certain observables (e.g., age, marital status, gender) relate to the demand for improved safety technologies but unobservable preference heterogeneity is not revealed in this exercise. The analysis is still of interest since observing the combined effects of these forces on accidents (claims) in conjunction with the analysis of the following two subsections help us to better understand the various issues raised in this paper. We first employ the following Probit model:

$$\begin{aligned} \Pr(claim_{it} &= 1 \mid airbag\_high_{it}, brake\_high_{it}, beh\_suv_i, bm_{it}, X_{it}) \qquad (46) \\ &= F(airbag\_high_{it}\beta_1 + brake\_high_{it}\beta_2 + veh\_suv_{it}\beta_3 + bm_{it}\beta_4 + X_{it}\beta_5) \end{aligned}$$

In Equation (46), $claim_{it} = 1$ when the insured i has filed a claim based on compulsory automobile liability insurance during the policy year t, otherwise $claim_{it} = 0$. F denotes the cumulative distribution function of the Probit regression, and is assumed to be normally distributed. The variables $airbag\_high_{it}$, $brake\_high_{it}$, and veh_suv_{it} are the safety technologies. bm_{it} is the bonus-malus value of the insured i at time t. The vector X_{it} denote the explanatory variables, including gender, marital status, age of the policyholder, vehicle age, the vehicle registration location, and a year dummy ($year2011$) to control the time effect. β's are the corresponding coefficients.

Table 4 shows that for the whole sample, as well as in each subsample, the coefficient on $airbag\_high$ is significantly negative. This finding differs from some previous research (e.g., Peterson, Hoffer, and Millner, 1995; Harless and Hoffer, 2003) which finds that drivers of vehicles equipped with airbags are more likely to be at fault in accidents. However, we find that the coefficient of $airbag\_high$ is significantly negative; i.e., drivers in a vehicle equipped with high quality airbag systems are less likely to cause accidents. In other words, our findings suggest that high quality airbag systems are associated with advantageous recruitment and any offsetting effect that may exist is not sufficiently strong to counteract the recruitment effect.

Table 4 also shows that the coefficient of $brake\_high$ is significantly negative in all groups of samples, which is at least not inconsistent with advantageous recruitment. Treating the high quality braking system as a higher level of PRT means that adoption per se of this technology should lead to a reduction in the probability of an accident. If there is an offsetting effect, this is not strong enough to reverse the accident mitigation effect of the higher quality PRT. There could be an adverse recruitment effect in this case if it is not strong enough to reverse the net effect of the two forces described above. However, we cannot conclude one way or the other about the recruitment effect from these results.

The coefficient for veh_suv is not significant. In other words, we do not find evidence that choice of an SUV implies a change in the driver's probability of an accident.

As expected, individuals with a higher bonus-malus coefficient have a higher probability of sustaining an accident. On average, females have a higher accident rate than males. Married individuals have a lower probability than singles. For different age groups, we find that the young policyholders (younger than 25 years old) have the highest probability of sustaining an accident. New cars and cars with age younger than 4 years old have a higher probability of sustaining an accident than do cars older than 4 years old in the whole sample and the subsample without voluntary third party bodily injury insurance. The differences among different car age groups are not significant in the subsample with voluntary third party bodily injury insurance.

4.3 Statistical Evidence: Part 2 - Panel Data Estimates

In this section we use the data only for those vehicle owners who were present in both years of the sample period and purchased a new (different) vehicle in the second year. By tracking whether they retained the same quality safety technologies (LMT and PRT levels) or upgraded or downgraded we can estimate the impact of these decisions on claims (accidents). Assuming that preferences do not change over the two years, any observed change in claim experience resulting from a change in equipment is independent of recruitment effects. If an individual purchases a new vehicle with an upgraded braking system AND does not adjust behaviour, then we should observe a reduction in claim probability. If there is offsetting behaviour (i.e., the individual drives less carefully), then this will mitigate the intrinsic safety effect of the improved braking system. As long as the mitigation is only partial, there will still be a negative relationship between the adoption of the higher quality brake system and accidents caused and so a subsidy is in order. The size of the subsidy, however, should be reduced according to the extent of any mitigation effect. If the mitigation effect is more than 100%, then we would observe a positive relationship between purchasing a vehicle with an improved braking system and the probability of a claim. In this case a tax on cars with upgraded brakes would be in order.

If an individual purchases a new vehicle with an improved airbag system, there is no intrinsic effect on safety and so any change in claim experience may be considered attributable to behavioural change. From the theoretical perspective, we do expect at least a small increase in the probability of claim. The size of the offsetting effect would determine the size of the appropriate tax to deal with the negative externality.

As noted in section 4 (Data), there are 17,002 individuals who switched vehicles in 2012. The relevant data on these vehicles, as well as other variables used in this section, is summarized in Tables 5 and 7 with definitions of "new" variables given in Table 6. By "new" cars, we mean new purchases including individuals who purchase a used vehicle in 2012. From Table 7, we see that the age of newly purchased vehicles is, on average, 2.25 years less (newer) than the vehicles previously owned. A larger fraction of new vehicles had reduced quality braking systems (13.4% with increased quality and 17.8% reduced quality) while more vehicles had increased quality airbags (9.2% with increased quality and 5.5% decreased quality). 5.48% of new purchases represent a change from a car to a SUV while 2.25% involved the reverse change.

We estimate the following logistic regression equation:

$$\log\left(\frac{1-p}{p}\right) = inc_{brk}\beta_1 + dec_{brk}\beta_2 + inc_{arbg}\beta_3 + dec_{arbg}\beta_4 + inc_s\beta_5 + dec_s\beta_6 \quad (47)$$

$$+ \quad < \; < int\_safe\_size >> + \; delta\_carage\_\beta_7 + X\beta_X + \Delta Externality \quad (48)$$

and estimate separately the set of observations including an increase in claims in 2012 compared to 2011 (*riskier*) and those observations including a decrease in claims in 2012 compared to 2011 (*lessrisky*). The definition of "becoming *riskier*" includes: (1) *riskier_ clm*: no claim in first year and at least one claim in second year, (2) *riskier_ clmtimes*: claim times increase from first year to second year, (3) *riskier_ clmamt*: increase in dollar amount of claims. A similar set of definitions is used for the *lessrisky* variables.

The X vector includes variables already used (e.g., female, married, age2530,age3060, ageabv60, carage0, carage1to4, city, north, south, east. We also include regional differences in the safety variables which pose changes in the driving environment and so are described as $\Delta Externality$, which is a vector that includes the change in the mean value of changes in safety equipment of vehicles, the mean value of the number of tickets issued in the registration county, and so forth as described in Table 6.

In order to use the Logistic Regression, we compare separately those individuals displaying a higher experience of claims to the those with no change in claims. So, for example, we define the dummy variable *riskier_ clm* which equals 1 for any individual who experienced a claim in 2012 but did not in 2011 and assign a value of 0 otherwise. Alternatively, we compare those individuals displaying a reduced claims' experience to those with no change in claims. In this case we define the dummy variable lessrisky_clm which equals 1 for any individuals who experienced a claim in 2011 but not in 2012 and assign a value of 0 otherwise. We then regress these dummy variables against the various independent variables to determine whether adoption of either a higher or lower quality brake system (or airbag system) is statistically related to an increased or decreased risk of making claims (i.e., being the cause of an accident resulting in a third party claim for bodily injury). For the sake of robustness, we also use as dependent variable a change in the amount of claims created between the two years and the number of times a claim is made)[13]. We find no important differences between the results.

In our regression that investigates possible reasons for increased claims (riskier driving - Table 8), we find a statistically significant negative relationship between vehicles with decreased quality airbag systems. This is consistent with classic offsetting behaviour as people who become more exposed to risk of injury in their vehicles through purchase of a vehicle with lower quality airbag system are less likely to create an accident claim. The reverse, however, does not hold; i.e., there is no statistically significant relationship between the variable inc_{arbg} and claims. There is no statistically significant relationship between our measures of riskier driving and either the purchase of a vehicle with increased or decreased quality braking systems. Of course, this does not mean there isn't a change in people's driving behaviour. For example, a person who purchases a new vehicle with improved brake system may drive less carefully because of this feature while the intrinsic improvement in safety from the improved brakes effectively mitigates the reduced caution in driving behaviour and so offsetting behaviour may be present.

In our regression that investigates possible reasons for a reduction in claims (less risky driving - Table 9), there is a statistically significant relationship between the reduction in claims and purchase of a vehicle with an improved brake system. As noted at the beginning of this section, such a result is consistent with some offsetting behaviour if the extent of the offsetting behaviour is not so strong as to reverse the beneficial effect on safety from the improved braking technology. In any case, if the net effect is an improvement in safety (reduction in claims), then a subsidy on vehicles with improved brake systems is warranted. Perhaps surprisingly, there is no statistically significant relationship between the purchase of a vehicle with a lower quality braking system and any of the measures of improved (reduced) claims experience. This may be explained by individuals who purchase vehicles with lower quality braking driving with even greater care to offset the intrinsic reduction in safety from the change in brake system.

There are a few results of interest from other variables which are significantly statistically related to the dependent variables. The change in car age (i.e., the bigger the difference - typically negative - in the age of the newly purchased car and the car owned in 2011) is positively related to our measures of reduced level of claims (e.g., $lessrisky\_clm$) and negatively related to our measures of increased level of claims (e.g., $riskier\_clm$), although not statistically significantly in the latter case. This could be due to drivers becoming more careful in how they drive their "newer" vehicles and/or due to overall increase

[13] There are only a few instances, for example, of a person having one claim in 2011 and two claims in 2012 that would trigger a value of 1 for the dummy variable $riskier\_ clmtimes$.

safety (e.g., unmeasured characteristics such as better overall handling characteristics).

5 Discussion

A large number of empirical studies have investigated the effect of improvements in safety technologies over a wide range of phenomenon. We have developed a model using a classification of such technologies based on whether adopting the technology leads, ceteris paribus, to a reduction in the probability of an accident or, conditional on an accident occurring, reduces the extent of the consequences or size of loss due to the accident. We refer to the former as a probability reduction technology (PRT) and the latter as a loss mitigation technology (LMT). Our model also considers two possible sources of heterogeneity among potential adopters of improved technologies. In one case we consider that individuals differ by their perceived loss due to an accident while in the other, some individuals display a higher cost of taking precautions to avoid accidents (i.e., effort to drive more safely). In order to understand the relative safely levels of drivers who end up adopting improved technologies compared to those who do not, both before and after adoption, one must understand the reason for adoption (i.e., the source of heterogeneity in preferences). We investigated these issues theoretically and discuss in what follows how to draw policy conclusions based on observations driven by the various possibilities. We also examine the challenges in interpreting data linking accident rates to adoption decisions both from a theoretical perspective and through our empirical application.

Vehicle owners (drivers) are assumed to differ according either to their perceived loss or concern with being involved in an accident or to their personal cost of taking preventive actions (i.e., the extent of safe driving habits). These two dimensions of the model help in unraveling the relationship between riskiness of adopters of the different types of safety technologies both before and after adoption of improved safety technologies. For example, individuals who perceive higher losses due to accidents will, at least ex ante to adoption, drive more carefully and so be less likely to be involved in accidents. Such drivers will more likely adopt either an LMT or PRT. If the extent of any offsetting behaviour is not too large, then adopters will continue to display lower accident risk levels ex post to adoption. However, individuals who possess a higher cost to safe driving behaviour will also be more likely to adopt either type of technology but have higher accident rates ex ante. These individuals who adopt an improved LMT will have further incentive to reduce their safe driving habits and so have an even higher accident rate ex post to adoption. The effect of adopting a higher quality PRT for either type of driver depends on whether the PRT is a substitute or complement to safe driving behaviour (i.e., the offsetting effect may be the typical one of reducing safe driving or have the opposite effect of increasing safe driving behaviour). Interpreting the relationship between accident rates and adoption of safety technologies - the so-called recruitment effect - requires careful analysis of the relationship between both ex ante and ex post accident rates of adopters versus non-adopters. It is important to understand these relationships in order to draw appropriate conclusions about the extent of offsetting effects from empirical analysis.

The classic interpretation of a negative externality arising from the offsetting effect due to adoption of an LMT (such as seatbelts) arises from the reasonable presumption that the inherent reduction in the negative consequences due to accidents reduces the marginal value to exerting safe driving behaviour. More care must be made when considering adoption of $PRTs$. If, for example, the source of a positive relationship between accident rates and adoption of a PRT is due to a preference by those with a higher cost of careful driving wanting to balance their higher risk of accident by use of the improved technology, then it does not necessarily follow that there will be a negative externality effect resulting from the improved technology despite the observed higher accident rate of adopters compared to nonadopters. If the PRT is complementary to individuals' own safe driving efforts, then there will be an even greater impact on overall safety even if the accident rates of adopters is observed to be higher than nonadopters. This will happen if the combined effect of the PRT and enhanced safe driving efforts does not make adopters accident rates fall below that of nonadopters which, given the assumption that adopters have a higher cost of precaution, is possible. Even if the PRT and safe driving efforts are substitutes, the net effect on adopters' accident rates may still lead to a reduction in the probability of them causing an accident. Therefore, despite a perception of an offsetting effecting, there may exist an overall positive externality created by such technologies and so, from a welfare perspective, such a technology should be subsidized in such cases. Of course, if the overall effect of adoption of a PRT and resultant change in driving behaviour leads to an increase in adopters' probability of causing an accident, then a tax on the technology is in order.

Suppose, on the other hand, that the reason for those who adopt a PRT is that they perceive a higher loss due to any accident that may occur. Such individuals would, ex ante to adoption, display lower accident rates than nonadopters. If the PRT is a complement to safe driving habits, then a reverse offsetting effect would occur and the accident rate of adopters would be even lower ex post to adoption. If the PRT and safe driving habits are substitutes, then the usual offsetting effect can be expected. However, the ex post accident rate for adopters may remain below that for nonadopters. This could be observed even if the offsetting effect leads to an increase in the accident rate of adopters provided the offsetting effect was not so strong as to lead to adopters to have a higher (ex post) accident rate than the (ex ante and ex post) accident rate of nonadopters. In this scenario, the

PRT creates a negative externality and so should be taxed even though adopters display a lower accident rate than that of nonadopters.

As is evident from the above discussion, as well as the formal propositions in this paper, one must take care in drawing conclusions from observations of accident rates and vehicle (safety) characteristics in regards to the presence and extent of offsetting behaviour in conjunction with recruitment effects as well as the type of heterogeneity of preferences that exists in the population of vehicle owners. This is crucial information in determining appropriate policy considerations in regards to the appropriate tax (or subsidy) to apply to safety technologies as well as deciding which technologies to make mandatory. As has been noted before (e.g., Harless and Hoffer, 2003), data which allows one to follow individuals' driving records and accident histories over time can be very useful in this regard. We have analyzed an unbalanced panel data set to illustrate how our theoretical analyses can guide one to understand better these important issues. Ignoring the panel nature of the data, simple correlations indicate a negative relationship between accident rates and both the adoption of higher quality airbags and higher quality brake systems. According to the classic offsetting hypothesis, adopting a higher quality LMT is expected to lead to a reduced level of safe driving care and so, ignoring possible recruitment effects, a positive relationship between the quality of the technology and accident rates. The observed negative correlation points towards advantageous recruitment (i.e., safer or less risky drivers choose the better technology).

Drawing conclusions about $PRTs$ is more complicated. Adoption of a higher quality PRT by its nature leads to a reduction in the probability of an accident provided there is no overwhelming offsetting effect. If the PRT is a complement to safe driving behaviour, then one expects a reverse offsetting effect which strengthens the negative relationship between the level of PRT and accident rate. However, if the reason for individuals purchasing a higher quality PRT is due to having a higher cost of (own) precaution, the recruitment effect may look different depending on whether contemporaneous or historical accident rates are being observed. From our empirical analysis, we find a negative correlation using either current or past measures of accident rates (riskiness of drivers) and so again the negative correlations point toward advantageous recruitment.

There are many challenges to any study about the effects of safety vehicles for vehicles that also apply to our work. As mentioned earlier in the paper, some safety features may display both LMT and PRT effects. This is likely for higher quality brake systems. Also, although our example of a LMT (high quality airbag) presumably decreases the harm to occupants in any substantial impact, minor accidents may involve higher financial losses for such vehicles as more complex airbag systems, if triggered unnecessarily, may be more expensive to reset. Thus, the implication of the classic offsetting hypothesis that such a safety device would incentivize drivers to be less cautious may in fact be incorrect.

Another important challenge is to consider the role of insurance and traffic enforcement. Safer vehicles may be less expensive to insure and this provides an incentive to purchase such vehicles and so at least in part behaves as an appropriate subsidy, albeit not necessarily in a complete manner. Also, insurers may use experience rating in a way that lessens moral hazard, for example, by people who purchase vehicles with enhance $LMTs$. To be fully effective in welfare terms, however, such experience rating would need to be designed according to vehicle and driver types. Also, traffic enforcement is not likely to involve policies, including fines, which differ according to safety features of vehicles.

More generally, when we refer to the individual's level of precaution we mean things such as attentiveness to road hazards while driving, maintaining alertness, driving at safe speeds, and so forth. These are assumed unobservable to the social planner (or government). Our analysis is designed to consider how such choices create externalities for others under various scenarios of available PRT and LMT technologies and for individuals with two possible sources of heterogeneous preferences which lead them to value such technologies differently. Although certainly worthy of future research, we do not consider the may direct and indirect measures used for imperfectly observing (and controlling) individual choices of level of care or precaution. These include police enforcement of traffic regulations (fines for speeding, following too closely, etc.) and measures such as experience rating by insurers, that others have studied (e.g., Boyer and Dionne, 1987). We leave aside these sorts of issues, although they are all well worth exploring in future work.

Although our model advances the literature by allowing for two dimensions of preferences (cost of own effort towards safe driving and size of loss due to an accident), there are many more possible dimensions that one could explore. Some of these may be approximated reasonably well by our chosen dimensions, but others deserve greater attention. For example, our objective function implies risk neutrality. However, allowing for individuals to vary in their perceived size of loss due to an accident may approximate a difference in risk aversion with more risk averse individuals holding a higher degree of loss. Admittedly, though, the implications of risk aversion on choice of self-protection or level of safety technologies is a complicated matter. The difficulty of determining the effect of varying the degree of risk aversion on the optimal level of precaution is well known. It would also be difficult to determine the effect of risk aversion on choice of a PRT. Since increasing the degree of LMT reduces the size of loss and so increases income in the loss state of the world, this may pose less problematic. Allowing for differences in income levels would also create complications in our model.[14] We also do not explore the possibility of

[14] Our data set does not have information on income levels.

innate differences in driving ability that may be reflected in the probability of an accident occurring (i.e., the $D(p, \theta)$ function).

There are many other alternative assumptions one could make about preferences. We implicitly assume risk neutral expected utility preference. Many alternative behavioural models could of course also be explored. Our model does, however, allow for weighted probabilities. The factor $(1 + v)$ in the expected loss term, $D(p, \theta)(1 + v)L(\lambda)$, which reflects a multiplicative term on the size of the loss could also be treated as a weighting factor on the probability of the loss state. Other more heuristic models have also been suggested.

Another important consideration is whether individuals are well informed about the relative safety features of different vehicles. There are many such features to understand and trade off between models. Examples include visibility, handling, crash worthiness, relative effectiveness of the myriad safety features (including so-called nanny devices) that can be purchased between models of a given brand of vehicle and between brands. Moreover, people may consider other features of a vehicle important that may have to be traded off with safety features, such as storage compartments, comfort of seats, quality of sound system, etc..

Finally, it can be difficult to assess the extent to which a feature is advantageous in preventing high loss accidents. A good example is the decision to purchase a SUV. Although its size is an advantage in reducing the extent of harm to occupants should an accident occur, the size may be a disadvantage in avoiding an accident in the first place. Being both larger and having a higher centre of gravity implies a higher rollover risk as well as a longer stopping distance.

6 Conclusions

We have developed a model of decision making by owners/drivers of vehicles that allows for two sources of heterogeneity in preferences as potential reasons why people purchase vehicles with differing quality safety features. We also explicitly introduce two types of such safety features. One type, such as high quality airbag systems, offer greater protection against harms to individuals should an accident occur while the other, such as high quality brake systems, offer intrinsic reduction in the probability of being involved in an accident. We refer to these, respectively, as loss mitigation technologies (LMT) and probability reduction technologies (PRT). We show that the demand for these two types of technologies and the implications on the relationship between their adoption and accident probabilities both ex ante to adoption (recruitment effects) and ex post (recruitment plus offsetting behaviour effects) differs in interesting ways. We believe our model could, with extensions, be useful for studying the myriad of newly developed safety technologies for vehicles as well as in other domains involving changes to safety protocols and technology.

Using data from the Taiwan Insurance Institute (TII), supplemented with detailed information on insureds' claims and driving records, we illustrate our model with an empirical application involving these two types of safety features; i.e., quality of airbag systems (a LMT) and quality of braking systems (a PRT). Both simple correlations and cross-sectional regressions generated a negative statistical relationship between accident claims caused by drivers of vehicles and high-quality airbags or high-quality brake systems of those vehicles.[15] Consider first the case of airbags. Although causality cannot be inferred from these results, they are at least consistent with advantageous recruitment (i.e., less risky drivers are more likely to obtain vehicles with higher quality airbags). Given the classical offsetting effect due to adoption of an LMT, which would generate a positive relationship between the safety feature of high-quality airbag and level of safe driving, this result in principle makes advantageous selection a plausible conclusion. Our regressions based on the subset of owners present in both periods reveal a negative statistical relationship between drivers becoming riskier and purchase of a new vehicle with lower quality airbags which is consistent with the classic offsetting hypothesis (for a LMT). There is, however, no complementary effect for drivers who have purchased new vehicles that have upgraded quality of airbags (i.e., there is no statistically significant relationship between inc_arbg and increased claims experience).

Our results point in the direction of advantageous recruitment for both high-quality airbags and high-quality brake systems, the LMT and PRT investigated here, and that any offsetting effect from the adoption of high-quality brake systems is not strong enough to reverse the inherent improvement in the accident rate due to the nature of the PRT. On the basis of this finding, one can make the case that a subsidy on this PRT would improve welfare.

7 Appendix

We now consider the scenario in which each individual chooses simultaneously his level of precaution, PRT and LMT. Given what we have learned for the case of being able to choose only one of PRT and LMT (i.e., singly), it is not surprising that performing comparative statics leads in many cases to ambiguous results. For the case of heterogenous cost of precaution (Model C1), we have that each individual chooses $\{p, \lambda, \theta\}$ to minimize

$$\Omega(p, \lambda, \theta) = D(p, \theta)L(\lambda) + (1 + \tau)c(p) + k_R(\theta) + k_M(\lambda) \tag{49}$$

[15]This is the case both for contemporaneous claims and historical claims as measured by the bonus malus measure.

For convenience, we assign variable numbers 1, 2, 3, to p, λ, θ, respectively, and so write the first-order conditions for the optimization problem as follows.

$$F_1(p, \lambda, \theta) = D_p L + (1+\tau)c' = 0 \tag{50}$$

$$F_2(p, \lambda, \theta) = DL_\lambda + k'_M = 0 \tag{51}$$

$$F_3(p, \lambda, \theta) = D_\theta L + k'_R = 0 \tag{52}$$

Upon totally differentiating the above system we get, using standard notation,

$$\begin{bmatrix} F_{11} & F_{12} & F_{13} \\ F_{21} & F_{22} & F_{23} \\ F_{31} & F_{32} & F_{33} \end{bmatrix} \begin{bmatrix} dp/d\tau \\ d\lambda/d\tau \\ d\theta/d\tau \end{bmatrix} = \begin{bmatrix} -c'(p) \\ 0 \\ 0 \end{bmatrix} \tag{53}$$

where

$$F_{11} = D_{pp}L + (1+\tau)c'' > 0,\ F_{12} = D_p L_\lambda > 0,\ F_{13} = D_{p\theta}L? \tag{54}$$

$$F_{21} = D_p L_\lambda > 0,\ F_{22} = DL_{\lambda\lambda} + k''_M > 0,\ F_{23} = D_\theta L_\lambda > 0 \tag{55}$$

$$F_{31} = D_{p\theta}L?,\ F_{32} = D_\theta L_\lambda > 0,\ F_{33} = D_{\theta\theta}L + k''_R > 0 \tag{56}$$

Note that the sign of $F_{13}(F_{31})$, indicated by ?, is the same as the sign of $D_{p\theta}$ and so depends on whether precaution and the PRT are substitutes or complements. From the above, we have the following comparative statics results. Again, $|F| > 0$ and so signs are the same as the signs of the numerators.

$$\frac{d\lambda}{d\tau} = c'[(D_p L_\lambda)(D_{\theta\theta}L + k''_R) - (D_{p\theta}L)(D_\theta L_\lambda)]/\,|F| \tag{57}$$

The term $(D_p L_\lambda)(D_{\theta\theta}L + k''_R) > 0$ contributes to a positive relationship between λ and τ. It follows that $\frac{d\lambda}{d\tau} > 0$ if $D_{p\theta} \leq 0$ (i.e., if own care and the PRT are complements). This follows since a higher cost of p reduces the incentive to provide own care which in turn reduces the effectiveness of θ (the PRT) when they are complements. Lowering both p and θ leads to an increase in the probability of loss (D) which in turn increases the marginal value of the LMT and so any reduction in θ (in addition to a reduction in p) reinforces the incentive to increase λ. However, if precaution and the PRT are substitutes, then a lower choice of p due to a higher cost would lead to a higher productivity of θ which would lead to a reduction in the loss probability. This is demonstrated by the following result and explanation.

$$\frac{d\theta}{d\tau} = -c'[(D_p L_\lambda)(D_\theta L_\lambda) - (D_{p\theta}L)(DL_{\lambda\lambda} + k''_M)]/\,|F| > 0 \tag{58}$$

The second term in brackets represents a positive effect of an increase in τ on θ when p and θ are substitutes ($D_{p\theta} > 0$). This accords with intuition since in this case any reduction in (more costly) p makes θ (PRT) more effective in reducing the probability of loss. If p and θ are complements ($D_{p\theta} < 0$), then any reduction in p reduces the effectiveness of θ and so in that case the second term represents a negative effect of an increase in τ on θ. Note that any increase in the probability of loss due to either a decrease in p or θ would increase the marginal value of the LMT. Given these instruments (λ and θ) are chosen simultaneously, an induced increase in λ would reduce the size of the loss and so have a a negative effect on the marginal productivity of θ. The first term in square brackets, $(D_p L_\lambda)(D_\theta L_\lambda)$, is positive and so captures this negative effect of an increase of τ on θ. Therefore, the net effect of an increase in τ on θ depends on the relative strength of all of these effects. Notice that this second unambiguously positive effect is stronger the higher is the effect of increasing λ on the size of loss (i.e. on the magnitude of $|L_\lambda|$) and in fact disappears as $L_\lambda \to 0$ which corresponds to the results when θ is the only choice variable.

$$\frac{dp}{d\tau} = -c'[(DL_{\lambda\lambda} + k''_M)(D_{\theta\theta}L + k''_R) - (D_\theta L_\lambda)^2]/|F| > 0 \tag{59}$$

The part $(DL_{\lambda\lambda} + k''_M)(D_{\theta\theta}L + k''_R)$ (in square brackets) is positive and contributes to a negative relationship between τ and p, the effect one would expect from simply having the cost of own care increasing in τ. However, the term $-(D_\theta L_\lambda)^2$ reduces this effect and, if strong enough, may even lead to a positive relationship between τ and p.

Proposition 7. *Suppose individuals differ according to cost of precaution and choose (simultaneously) levels of PRT (θ) and LMT (λ) along with their level of precaution (p) to minimize expected loss. Individuals who face higher cost of precaution increase their level of LMT if the PRT is a complement to precaution (i.e., $D_{p\theta} < 0$). The effect is indeterminate if precaution and the PRT are substitutes ($D_{p\theta} > 0$). The relationship between cost of precaution and the other variables of interest (precaution, p, and the PRT,θ) are indeterminate.*

We now develop Model 3B in which the heterogeneity is due to differential size of loss should an accident occur. Recall that the objective function is

$$\Omega(p, \lambda, \theta) = D(p, \theta)(1 + \upsilon)L(\lambda) + c(p) + k_R(\theta) + k_M(\lambda) \tag{60}$$

and so the first-order conditions for the optimization problem are as follows.

$$F_1(p, \lambda, \theta) = D_p(1 + \upsilon)L + c' = 0 \tag{61}$$

$$F_2(p, \lambda, \theta) = D(1 + \upsilon)L_\lambda + k'_M = 0 \tag{62}$$

$$F_3(p, \lambda, \theta) = D_\theta(1 + \upsilon)L + k'_R = 0 \tag{63}$$

Upon totally differentiating the above system we get, using standard notation,

$$\begin{bmatrix} F_{11} & F_{12} & F_{13} \\ F_{21} & F_{22} & F_{23} \\ F_{31} & F_{32} & F_{33} \end{bmatrix} \begin{bmatrix} dp/d\upsilon \\ d\lambda/d\upsilon \\ d\theta/d\upsilon \end{bmatrix} = \begin{bmatrix} -D_pL \\ -DL_\lambda \\ -D_\theta L \end{bmatrix} \tag{64}$$

where

$$F_{11} = D_{pp}(1+\upsilon)L + c'' > 0,\ F_{12} = D_p(1+\upsilon)L_\lambda > 0,\ F_{13} = D_{p\theta}(1+\upsilon)L? \tag{65}$$

$$F_{21} = D_p(1+\upsilon)L_\lambda > 0,\ F_{22} = D(1+\upsilon)L_{\lambda\lambda} + k_M'' > 0,\ F_{23} = D_\theta(1+\upsilon)L_\lambda > 0 \tag{66}$$

$$F_{31} = D_{p\theta}(1+\upsilon)L?,\ F_{32} = D_\theta(1+\upsilon)L_\lambda > 0,\ F_{33} = D_{\theta\theta}(1+\upsilon)L + k_R'' > 0 \tag{67}$$

From the above, we have the following comparative statics results (noting that $|F| > 0$).

$$\frac{dp}{d\upsilon} = \left\{-D_pL[F_{22}F_{33} - (F_{23})^2] + DL_\lambda[F_{12}F_{33} - F_{13}F_{32}] - D_\theta L[F_{12}F_{23} - F_{22}F_{13}]\right\} / |F| \tag{68}$$

$$\frac{d\lambda}{d\upsilon} = \left\{D_pL[F_{21}F_{33} - F_{23}F_{31}] - DL_\lambda[F_{11}F_{33} - (F_{13})^2] + D_\theta L[F_{11}F_{23} - F_{21}F_{13}]\right\} / |F| \tag{69}$$

$$\frac{d\theta}{d\upsilon} = \left\{-D_pL[F_{21}F_{33} - F_{22}F_{31}] + DL_\lambda[F_{11}F_{32} - F_{12}F_{31}] - D_\theta L[F_{11}F_{22} - (F_{12})^2]\right\} / |F| \tag{70}$$

An increase in parameter ν leads to increased productivity of each choice variable. However, an increase in λ would reduce the marginal productivity of each of the other choice variables, (p, θ). Similarly, an increase in either p or θ would reduced the marginal productivity of λ. Finally, an increase in θ would decrease or increase the marginal productivity of p (or vice versa) depending on whether the two variables are substitutes or complements (i.e., whether $D_{p\theta}$ is positive or negative, respectively). Given these relationships, none of the comparative statics results can be signed definitively even if we make an assumption about the sign of $D_{p\theta}$.

Proposition 8. *Suppose individuals differ according to size of loss and choose (simultaneously) levels of PRT (θ) and LMT (λ) along with their level of precaution (p) to minimize expected loss. An increase in the loss size parameter (υ) increases the marginal productivity of each choice variable. However, any increase in λ reduces the marginal productivity of both precaution and the PRT. Moreover, any increase in one of precaution or the PRT increases or decreases the marginal value of the other depending on whether they are complements or substitutes. As a result, none of the signs of the comparative static relationships are determinate.*

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Table 1 Variable definitions: Set 1

Variables	Definition
claim	A dummy variable, it equals 1 when the insured have ever filed the claim in compulsory liability insurance within one policy year; otherwise it equals 0.
bm	The value of bonus malus coefficient
Dbm	A dummy variable, it equals 1 when the bonus malus coefficient of the insured is larger than 0.7; otherwise it equals 0.
brake_high	A dummy variable, it equals 1 when the insured vehicle is equipped with high quality brake system; otherwise it equals 0. The high quality brake system means the vehicle is equipped not only with anti-lock brake system, but also equipped with the traction control system\vehicle stability control system\acceleration slip regulation as well as down-hill assist control \the hill-start assist control.
airbag_high	A dummy variable, it equals 1 when the insured vehicle is equipped with high quality airbag system; otherwise it equals 0. The high quality airbag system means there are airbags equipped for both front seats and equipped for the back seats.
high_brk_high_abg	A dummy variable, it equals 1 when the insured vehicle is equipped with high quality brake system as well as high quality airbag system; otherwise it equals 0.
high_brk_low_abg	A dummy variable, it equals 1 when the insured vehicle is equipped with high quality brake system, but equipped with low standard airbag system; otherwise it equals 0.
low_brk_high_abg	A dummy variable, it equals 1 when the insured vehicle is equipped with low standard brake system, but equipped with high quality airbag system; otherwise it equals 0.
low_brk_low_abg	A dummy variable, it equals 1 when the insured vehicle is equipped with low standard brake system as well as low standard airbag system; otherwise it equals 0.
veh_suv	A dummy variable, it equals 1 when the insured vehicle is a sport utility vehicle (SUV); otherwise it equals 0.

Table 1 Variable definitions: Set 1 (continued)

Variables	Definition
female	A dummy variable, it equals 1 when the insured is female; otherwise it equals 0.
married	A dummy variable, it equals 1 when the insured is in marriage status; otherwise it equals 0.
age2530	A dummy variable, it equals 1 when the insured equals or older than 25 years old and younger than 30 years old; otherwise it equals 0.
age3060	A dummy variable, it equals 1 when the insured equals or older than 30 years old and younger than 60 years old; otherwise it equals 0.
ageabv60	A dummy variable, it equals 1 when the insured equals or older than 60 years old; otherwise it equals 0.
carage0	A dummy variable, it equals 1 when the insured vehicle is brand new; otherwise it equals 0.
carage1to4	A dummy variable, it equals 1 when the insured vehicle is more than 1 year and not over 4 years; otherwise it equals 0.
city	A dummy variable, it equals 1 when the insured vehicle is registered in city area; otherwise it equals 0.
north	A dummy variable, it equals 1 when the insured vehicle is registered in northern part of Taiwan; otherwise it equals 0.
south	A dummy variable, it equals 1 when the insured vehicle is registered in southern part of Taiwan; otherwise it equals 0.
east	A dummy variable, it equals 1 when the insured vehicle is registered in eastern part of Taiwan; otherwise it equals 0.

Table 2 Summary statistics

	Mean	Std	Obs
Panel A Whole sample			
claim	0.0100	0.0995	2255157
Dbm	0.2004	0.4003	2255157
airbag_high	0.0952	0.2935	2255157
brake_high	0.3939	0.4886	2255157
veh_suv	0.0771	0.2667	2255157
high_brk_high_abg	0.0012	0.0345	2255157
high_brk_low_abg	0.3927	0.4883	2255157
low_brk_high_abg	0.0940	0.2918	2255157
low_brk_low_abg	0.5122	0.4999	2255157
female	0.6008	0.4897	2255157
married	0.7618	0.4260	2255157
age2530	0.0440	0.2050	2255157
age3060	0.8306	0.3751	2255157
ageabv60	0.1144	0.3183	2255157
carage0	0.0668	0.2497	2255157
carage1to4	0.3227	0.4675	2255157
city	0.6850	0.4645	2255157
north	0.4405	0.4964	2255157
south	0.3040	0.4600	2255157
east	0.0421	0.2009	2255157
year2011	0.4724	0.4992	2255157

Table 2 Summary statistics (continued)

	Mean	Std	Obs
Panel B Sample with voluntary third party bodily injury insurance			
claim	0.0110	0.1045	1286309
Dbm	0.1975	0.3981	1286309
airbag_high	0.0909	0.2874	1286309
brake_high	0.3791	0.4852	1286309
veh_suv	0.0957	0.2941	1286309
high_brk_high_abg	0.0014	0.0374	1286309
high_brk_low_abg	0.3777	0.4848	1286309
low_brk_high_abg	0.0895	0.2854	1286309
low_brk_low_abg	0.5315	0.4990	1286309
female	0.6583	0.4743	1286309
married	0.7533	0.4311	1286309
age2530	0.0386	0.1926	1286309
age3060	0.8485	0.3586	1286309
ageabv60	0.1055	0.3072	1286309
carage0	0.0786	0.2691	1286309
carage1to4	0.3675	0.4821	1286309
city	0.6872	0.4636	1286309
north	0.4396	0.4963	1286309
south	0.3042	0.4601	1286309
east	0.0449	0.2070	1286309
year2011	0.4600	0.4984	1286309

Table 2 Summary statistics (continued)

	Mean	Std	Obs
Panel C Sample without voluntary third party bodily injury insurance			
claim	0.0086	0.0926	968848
Dbm	0.2042	0.4031	968848
airbag_high	0.1009	0.3012	968848
brake_high	0.4135	0.4925	968848
veh_suv	0.0524	0.2229	968848
high_brk_high_abg	0.0009	0.0302	968848
high_brk_low_abg	0.4126	0.4923	968848
low_brk_high_abg	0.1000	0.3000	968848
low_brk_low_abg	0.4865	0.4998	968848
female	0.5246	0.4994	968848
married	0.7731	0.4188	968848
age2530	0.0511	0.2202	968848
age3060	0.8069	0.3947	968848
ageabv60	0.1262	0.3320	968848
carage0	0.0511	0.2202	968848
carage1to4	0.2633	0.4404	968848
city	0.6821	0.4657	968848
north	0.4416	0.4966	968848
south	0.3036	0.4598	968848
east	0.0386	0.1925	968848
year2011	0.4887	0.4999	968848

Table 3 Correlation coefficients

	claim	Dbm	airbag_high	brake_high	veh_suv
claim	1.000				
Dbm	0.012***	1.000			
airbag_high	-0.005***	-0.004***	1.000		
brake_high	-0.004***	-0.072***	-0.253***	1.000	
veh_suv	0.0004	0.019***	0.036***	-0.144***	1.000

Table 4 Pooled Probit regression of compulsory liability claim

	Whole sample		With voluntary third party bodily injury insurance		Without voluntary third party bodily injury insurance	
	Est.	**P value**	**Est.**	**P value**	**Est.**	**P value**
Intercept	-4.7884	<.0001	-4.4624	<.0001	-5.1590	<.0001
airbag_high	-0.1805	<.0001	-0.1693	<.0001	-0.1643	<.0001
brake_high	-0.0540	0.0003	-0.0341	0.0681	-0.0866	0.0004
veh_suv	-0.0073	0.7748	-0.0329	0.2709	-0.0163	0.7348
bm	0.8938	<.0001	0.8982	<.0001	0.9788	<.0001
female	0.1328	<.0001	0.0563	0.0020	0.1750	<.0001
married	-0.1242	<.0001	-0.1592	<.0001	-0.0608	0.0230
age2530	-0.2767	<.0001	-0.3356	<.0001	-0.2875	0.0004
age3060	-0.3357	<.0001	-0.4301	<.0001	-0.3382	<.0001
ageabv60	-0.3321	<.0001	-0.3906	<.0001	-0.3768	<.0001
carage0	0.1226	<.0001	-0.0092	0.7863	0.2900	<.0001
carage1to4	0.1631	<.0001	0.0288	0.1319	0.3370	<.0001
city	0.0660	<.0001	0.0698	0.0004	0.0558	0.0253
north	-0.4957	<.0001	-0.5021	<.0001	-0.4619	<.0001
south	-0.0498	0.0039	-0.0728	0.0009	-0.0125	0.6587
east	-0.1529	<.0001	-0.1826	<.0001	-0.1057	0.0823
year2011	0.0152	0.2568	-0.0114	0.5006	0.0902	<.0001
-2LogL	250843.91		155185.99		95213.045	
Observations	2255157		1286309		968848	

Table 5 Overview of safety technology decisions (New vehicle purchases)#

	suv	suv+ABS	small	small+ABS
increase airbag	17	0	566	1
decrease airbag	4	0	414	0
	suv	suv+airbag	small	small+airbag
increase brake	13	0	1612	1
decrease brake	3	0	1912	0
no change	9754			

#There are 2,706 observations not accounted for in this table. They are distributed into many descriptive cells, too numerous to include here.

Table 6 Variable definitions: Set 2

Variables	Definition
delta_clm	equals *clm_2* minus *clm_1* (*clm_1* and *clm_2* are the dummy variables which represent whether there is claim filed in first or second year)
delta_clmtimes	equals *clmtimes_2* minus *clmtimes_1* (*clmtimes_1* and *clmtimes_2* represents the claim times in first year or in second year)
delta_clmamt	equals *clmamt_2* minus *clmamt_1* (*clmamt_1* and *clmamt_2* represents the claim amount in first year or in second year)
riskier_clm	A dummy variable which equals 1 if *delta_clm*>0, otherwise 0.
riskier_clmtimes	A dummy variable which equals 1 if *delta_clmtimes*>0, otherwise 0.
riskier_clmamt	A dummy variable which equals 1 if *delta_clmamt*>0, otherwise 0.
lessrisky_X	A dummy variable which equals 1 if *delta_X*<0, otherwise zero – for *X* = *clm, clmtimes, clmamt*
inc_brk	A dummy variable, it equals 1 when the car owner switched vehicle from a low quality brake system to a high quality brake system; otherwise it equals 0.
dec_brk	A dummy variable, it equals 1 when the car owner switched vehicle from a high quality brake system to a low quality brake system; otherwise it equals 0.
inc_arbg	A dummy variable, it equals 1 when the car owner switched vehicle from a low quality airbag system to a high quality airbag system; otherwise it equals 0.
dec_arbg	A dummy variable, it equals 1 when the car owner switched vehicle from a high quality airbag system to a low quality airbag system; otherwise it equals 0.
inc_s	A dummy variable, it equals 1 when the car owner switched vehicle to a sport utility vehicle (SUV); otherwise it equals 0.
dec_s	A dummy variable, it equals 1 when the car owner switched vehicle from a sport utility vehicle (SUV) to other type of vehicle; otherwise it equals 0.

*inc_brk*inc_s*	Interaction term = 1 if new vehicle has *inc_brk* and *inc_s*, otherwise = 0.
*inc/dec_X*inc/dec_s*	Completes the set of interaction terms as described above depending on increase or decrease either brk or arbg along with increase or decrease s
delta_carage	A variable which equals the age of the new vehicle (in year 2012) minus the age of the old vehicle (in year 2011).
deltam_brk	A variable which equals the mean value of high quality brake system vehicles in the registration administrative area corresponding to each vehicle in year 2012 minus the mean value of high quality brake system vehicles in the registration administrative area corresponding to each vehicle in year 2011.
deltam_arbg	A variable which equals the mean value of high quality airbag system vehicles in the registration administrative area corresponding to each vehicle in year 2012 minus the mean value of high quality airbag system vehicles in the registration administrative area corresponding to each vehicle in year 2011.
deltam_s	A variable which equals the mean value of sport utility vehicles (SUV) in the registration county corresponding to each vehicle in year 2012 minus the mean value of sport utility vehicles (SUV) in the registration county corresponding to each vehicle in year 2011.
deltam_tkt	A variable which equals the mean value of the number of tickets in the registration county corresponding to each vehicle in year 2012 minus the mean value of the number of tickets in the registration county corresponding to each vehicle in year 2011.
deltam_clm	A variable which equals the mean value of claim probability in the registration county corresponding to each vehicle in year 2012 minus the mean value of claim probability in the registration county corresponding to each vehicle in year 2011.

Table 7 Detailed Summary Statistics on Panel Data Set (New vehicle purchases)

	Mean	StD
delta_clm	0.0036	0.1401
delta_clmtimes	0.0034	0.1432
delta_clmamt	86.3870	61184.3400
riskier_clm	0.0116	0.1073
riskier_clmtimes	0.0116	0.1073
riskier_clmamt	0.0118	0.1081
increase_brake	0.1343	0.3410
decrease_brake	0.1781	0.3826
increase_airbag	0.0918	0.2887
decrease_airbag	0.0548	0.2275
increase_size	0.0565	0.2308
decrease_size	0.0225	0.1482
delta_carage	-2.2557	6.1281
female	0.5722	0.4948
married	0.7355	0.4411
age2530	0.0503	0.2187
age3060	0.8348	0.3713
ageabv60	0.1010	0.3013
carage0	0.1800	0.3842
carage1to4	0.3824	0.4860
city	0.6825	0.4655
north	0.4505	0.4976
south	0.2987	0.4577
east	0.0383	0.1919
delta_mean_ABS	0.0114	0.0105
delta_mean_airbag	0.0068	0.0035
delta_mean_suv	0.0046	0.0141
delta_mean_ticket	-0.0002	0.0462
delta_mean_clm	-0.0001	0.0014

Table 8 Logistic Regression (*riskier_clm/clmtimes/clmamt*)

	Model 1		Model 2	
	coef	P value	coef	P value
Intercept	-4.4502	<.0001	-114.6000	0.4636
inc_brk	0.0020	0.9935	0.0084	0.9731
dec_brk	-0.0357	0.8741	-0.0390	0.8628
inc_arbg	0.1114	0.8098	0.1154	0.8031
dec_arbg	-1.0528	0.0419	-1.0640	0.0399
inc_s	-0.0179	0.9763	-0.0204	0.9731
dec_s	0.5123	0.3447	0.5137	0.3435
inc_brk*inc_s	-0.1177	0.9165	-0.1180	0.9163
inc_brk*dec_s	-0.3477	0.7014	-0.3563	0.6944
dec_brk*inc_s	-0.7644	0.3740	-0.7590	0.3775
dec_brk*dec_s	0.9637	0.4112	0.9622	0.4120
inc_arbg*inc_s	-0.9362	0.4043	-0.9435	0.4006
inc_arbg*dec_s	-12.2443	0.9792	-12.2417	0.9792
dec_arbg*inc_s	1.3452	0.2689	1.3459	0.2686
dec_arbg*dec_s	1.5811	0.1947	1.6003	0.1895
delta_carage	-0.0160	0.2463	-0.0159	0.2498
female	0.0345	0.8153	0.0359	0.8083
married	-0.0721	0.6602	-0.0776	0.6370
age2530	0.4819	0.5307	0.4754	0.5364
age3060	0.3032	0.6736	0.3050	0.6718
ageabv60	0.7031	0.3428	0.7059	0.3409
carage0	0.1855	0.4266	0.1922	0.4111
carage1to4	0.0961	0.5972	0.0980	0.5905
city	-0.0379	0.8168	0.0128	0.9466
north	-0.5056	0.0525	4.8039	0.5231
south	0.1094	0.6906	-4.6704	0.4875
east	-1.3178	0.0409	-2.1767	0.1228
deltam_brk	-1.3960	0.9111	1.0591	0.9374
deltam_arbg	-24.9420	0.5106	-15.5020	0.6947
deltam_s	1.7572	0.8601	3.0193	0.7748
deltam_tkt	1.6056	0.5267	1.6441	0.5387
deltam_clm	21.1059	0.7637	14.1497	0.8588
airbag_high_2	-0.1762	0.6416	-0.1784	0.6376

brake_high_2	0.1008	0.5996	0.0997	0.6038
veh_suv2	0.0920	0.8186	0.1011	0.8011
mean_brk 2			279.4000	0.4790
mean_arbg2			0.0000	.
mean_suv 2			-4.4810	0.5986
mean_tkt2			0.4901	0.8459
mean_clm2			9.4466	0.9117

Table 9 Logistic Regression (*lessrisky_clm/clmtimes/clmamt*)

	lessrisky_clm		lessrisky _clmtimes		lessrisky _clmamt	
	coef	P value	coef	P value	coef	P value
Intercept	-3.9595	<.0001	-3.9595	<.0001	-3.9614	<.0001
inc_brk	0.4300	0.0786	0.4300	0.0786	0.4851	0.0440
dec_brk	-0.0178	0.9462	-0.0178	0.9462	-0.0188	0.9432
inc_arbg	0.4494	0.1306	0.4494	0.1306	0.4586	0.1227
dec_arbg	-0.4896	0.2994	-0.4896	0.2994	-0.5199	0.2701
inc_s	-1.3866	0.1976	-1.3866	0.1976	-0.9595	0.2663
dec_s	-0.4842	0.6326	-0.4842	0.6326	0.2327	0.7482
inc_brk*inc_s	-12.7069	0.9848	-12.7069	0.9848	-13.0072	0.9849
inc_brk*dec_s	-0.0675	0.9627	-0.0675	0.9627	-0.8231	0.5123
dec_brk*inc_s	1.0315	0.4117	1.0315	0.4117	0.2878	0.7817
dec_brk*dec_s	-11.9444	0.9930	-11.9444	0.9930	-12.6209	0.9923
inc_arbg*inc_s	-0.1694	0.8941	-0.1694	0.8941	0.5351	0.6124
inc_arbg*dec_s	-12.8803	0.9896	-12.8803	0.9896	-13.5697	0.9889
dec_arbg*inc_s	2.9505	0.0567	2.9505	0.0567	2.5654	0.0685
dec_arbg*dec_s	-12.1934	0.9917	-12.1934	0.9917	-12.5094	0.9913
delta_carage	0.0323	0.0660	0.0323	0.0660	0.0311	0.0730
female	0.1840	0.3177	0.1840	0.3177	0.2202	0.2287
married	-0.1141	0.5676	-0.1141	0.5676	-0.1545	0.4297
age2530	-1.4930	0.0150	-1.4930	0.0150	-1.4943	0.0148
age3060	-1.0563	0.0157	-1.0563	0.0157	-1.0394	0.0174
ageabv60	-1.4403	0.0080	-1.4403	0.0080	-1.3237	0.0130
carage0	0.9162	0.0006	0.9162	0.0006	0.8640	0.0011
carage1to4	0.1536	0.4855	0.1536	0.4855	0.1541	0.4791
city	-0.0788	0.7023	-0.0788	0.7023	-0.0527	0.7968
north	-0.0221	0.9386	-0.0221	0.9386	-0.0350	0.9021
south	0.3672	0.2075	0.3672	0.2075	0.3439	0.2333
east	-0.0244	0.9587	-0.0244	0.9587	-0.0450	0.9238
deltam_brk	-27.1920	0.0619	-27.1920	0.0619	-26.9912	0.0604
deltam_arbg	44.5352	0.2072	44.5352	0.2072	42.5135	0.2275
deltam_s	-30.1583	0.0050	-30.1583	0.0050	-29.1234	0.0064
deltam_tkt	3.5103	0.2190	3.5103	0.2190	3.7310	0.1857
deltam_clm	158.8000	0.0296	158.8000	0.0296	166.4000	0.0191