The Use of Annual Mileage as a Rating Variable

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Abstract

Auto insurance companies are at a crossroads. Several variables commonly used, such as gender and territory, are being questioned by regulators. Insurers are being pressured to find new variables that predict accidents more accurately and are socially acceptable. Annual mileage seems an ideal candidate. The recent development of GPS systems, on-board computers, and telematics devices, and the rapid decrease in price of the new technologies, should induce carriers to explore ways to introduce Pay-As-You-Drive insurance.

We use the unique database of a major insurer in Taiwan to investigate whether annual mileage should be introduced as a rating variable in third-party liability insurance. We find that annual mileage is an extremely powerful predictor of the number of claims at-fault. Its significance, as measured by Wald's chi-square and its associated p-value, by far exceed that of all other variables, including bonus-malus. This conclusion applies independently of all other variables possibly included in rating. The inclusion of mileage as a new variable should, however, not take place at the expense of bonus-malus systems; rather the information contained in the bonus-malus premium level complements the value of annual mileage. An accurate rating system should therefore include annual mileage and bonus-malus as the two main building blocks, possibly supplemented by the use of other variables like age, territory, and engine cubic capacity. While Taiwan has specific characteristics (high traffic density, mild bonus-malus system, limited compulsory auto coverage), our results are so strong that we can confidently conjecture that they extend to all affluent countries.

1. Introduction

Auto insurers, in order to remain competitive in risk selection and pricing, are constantly seeking better ways to measure risk. To this end, they adopt numerous rating variables – and, when unavailable, proxy variables – in order to better gauge how risky each particular customer is.

As is typical in American automobile third-party liability insurance, a major carrier uses a large number of variables in rating, including age, sex, and marital status of principal driver (with unmarried males paying a surcharge until the age of 30, unmarried females until 25), make and model of car,

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territory (at zip code level), claims and traffic violations history, and use of car. The main categories for car use are pleasure, commuting, business, farm use, military. Commuters have to estimate the distance between home and work or school, as well as an estimate of total annual mileage. While a precise mileage estimation has to be provided, the company only uses a single cut-off point in rating, at 7,500 miles per year.

Representatives of the company privately acknowledge that they have few tools to ensure a truthful statement of variable values by policyholders. The policy wording contains a statement that any person who knowingly attempts to defraud the insurer with an application containing false information can be subject to a fine and possible imprisonment. Insurers occasionally phone policyholders to obtain verbal verification of mileage statements. However, companies cannot deny a claim if it is demonstrated that the policyholder was not truthful in reporting mileage, nor can they increase premiums retroactively. Consumer fraud and the inability of insurers to keep track of key lifestyle and driving habits of their customers are estimated to create over $16 billion in premium losses (called premium "leakage"), or nearly 10% of personal auto premium written (Insurance Services Office, 2008). The main fraud categories are misrepresentation of garaging addresses and youthful drivers, and understatement of annual mileage.

In May 2012, the company introduced in Pennsylvania a voluntary program to monitor mileage, using a telematics device (telematics is defined here as the technology of sending, receiving, and storing information via telecommunication appliances in vehicles). Using the catchy slogan "Just have your car send us your driving habits", the rating plan involves the use of a transmitter, that comes factory-installed in all new vehicles sold by the largest US car manufacturer, or can be professionally installed on existing cars as replacement of the rearview mirror at a cost of $100. A required subscription costing $200 per year provides automatic crash response, emergency services, roadside and stolen vehicle assistance, and diagnostic and maintenance information. Additional services such as hands-free calling and GPS navigation can be purchased at an additional price. Odometer readings are recorded, and e-mailed monthly to the subscriber and the insurer. Upon enrollment in the program, all insureds receive a 5% discount on liability, comprehensive, collision, and medical payments coverages. As odometer readings become available, a premium discount is offered at each renewal, for instance 32% for 3,500 annual miles, 13% for 11,000 miles, 5% for 15,000 miles. If the policyholder had his premium based on self-reported annual mileage under 7,500, and if the actual mileage exceeds that threshold, the next premium is increased.

This company uses the telematics device only to record effective mileage. Other companies monitor other driving habits, such as the use of the car between midnight and 4 a.m., speeds over 80 miles per hour, as well as acceleration and breaking behavior and the type of roads travelled (urban, country, motorway) (Muermann and Kremslehner, 2012). Premiums may be adjusted monthly, semi-annually, or annually. An international consulting firm (Ptolemus Consulting Group, 2012) estimates that, world-wide in 2012, telematics-based insurance policies are in effect for more than two million subscribers.

Auto insurance carriers may be at a crossroads concerning the classification variables they use. Regulators are questioning the use of some traditional variables like sex and territory, and request more accurate criteria. Insurers have been reluctant to use annual mileage, despite its obvious correlation with claims, due to their inability to verify policyholders' statements, and the relative easiness to tamper with odometers. This had led them to use proxy variables like the use of the car or the distance between home and work. Butler (2006) argues that no less than 12 widely used rating variables can be considered as proxies for odometer miles: sex, car age, previous accidents at-fault and not-at-fault, credit score, zip code, income, military rank, existence of a prior insurer, premium payment by installments, years with same employer, collision deductible, and tort rights. This situation may change rapidly, due to the development of telematics, on-board computers, sophisticated GPS transmitters, tampering-resistant odometers, and the fast decrease in cost of these new technologies.

In this research we investigate the impact of the use of mileage as a rating variable, using unique data originating from Taiwan. As in that state the leading brand of cars also owns an extended network of repair shops that customers visit for routine maintenance and oil changes, data that include driver classification variables, claims, and annual mileage, were available for over a quarter million vehicle-years. A regression study analyzes the importance of annual mileage as compared to other rating variables used in Taiwan. A model developed by Taylor (1997) is applied to evaluate the impact of mileage on the Taiwanese Bonus-Malus system.

Note that we do not consider Pay-at-the-Pump insurance, replacing premiums paid to insurance companies by a surcharge per gallon of gas at the pump. This approach would revolutionize auto insurance, and has a very different set of advantages and disadvantages. We are discussing here the pros and cons of using annual mileage as a rating variable in traditional insurance, as a replacement or as an addition to variables currently used.

2. Statistical Studies

It is intuitively obvious that annual mileage positively correlates with claim frequencies, since each mile a car travels creates a small chance of an accident. The use of annual mileage as a rating variables has long been recommended by actuarial studies, dating as far back as Bailey and Simon (1960)'s seminal paper. Several statistical studies have confirmed this conjecture: more time spent on the road translates into more traffic incidents, and more situations leading to claims. The average number of claims significantly increases with annual mileage, but not proportionally – there are diminishing "returns". Doubling annual mileage increases the claim frequency, but does not double it. This could be explained by the fact that high-mileage users are more experienced, or do more of their driving on low-risk highways rather than high-risk urban areas. Lemaire (1985) surveyed 3,995 policyholders of a Belgian company. With an average annual distance driven of 15,344 kilometers, claim frequencies increased from 5.84% for policyholders driving less than 5,000 km/year to 10.44% for an annual distance in excess of 30,000 km. The variable "annual distance travelled" proved to be highly significant in a regression explaining the number of claims. Only claims history proved to be more significant. The inclusion of annual mileage in regression allowed for the deletion of variables that would be difficult to use in rating such as the number of not-at-fault claims, the age of the car, and the type of insurance coverage selected.

Ferreira and Minikel (2010) merged data from the Massachusetts Commonwealth Automobile Reinsurer (an industry-operated entity that collects rate-making data for all policies issued in the state) and odometer readings recorded by the Registry of Motor Vehicles during compulsory annual safety inspections. They were able to analyze 2.87 million car years of exposure for policy year 2006, covering vehicles driven an aggregate of 34 billion miles, and found that claim frequencies increase with mileage, in a less-than-proportional way. A three-fold increase in annual mileage, from 10,000 to 30,000, results in a claim frequency increase that less than doubles, from 5% to 8%.

Litman (2011) matched mileage readings collected during mandatory emission checks in the Vancouver region with individual vehicles' insurance claim records, for more than 500,000 vehicle-years. Crash rates for all accidents (at fault or not) were found to increase from 4% for cars driving less than 5,000 kilometers per year, to around 8% in the 20,000 – 25,000 km range, and slightly less than 10% once the annual number of kilometers driven exceeds 35,000. Again, the relationship was found to be less-than-proportional, as the claims rate per kilometer driven decreases.

3. Using Mileage in Rating: a Controversial Issue

A large body of research addresses the advantages and disadvantages of mileage-based rating, usually abbreviated as PAYD (Pay-As-You-Drive). Interestingly, studies are usually sponsored by lobbying groups, and have not found their way into the peer-reviewed insurance or actuarial literature. PAYD is supported by environmentalists and associations advancing the interests of females, seniors, and low-income groups. For instance, NOW, the National Organization for Women, claims than females are discriminated against by the current pricing scheme. In the United States, females pay a lower premium than men, but only up to the age of 30. There is no premium differentiation after 30. NOW asserts that, as females drive significantly fewer miles than men (10,143 vs 16,553, according to the 2005 federal household transportation survey), pricing is discriminatory (Butler, 2006).

Groups that resist PAYD include the oil industry (due to the likely decrease in overall mileage driven and consequent reduction in oil consumption), and some segments of the insurance industry, as it requires changes in their practices and may decrease profits by reducing total premiums. Some insurers argue that social benefits are much larger than benefits to individual insurers. Most of the benefits of PAYD (reduced traffic congestion and pollution, and some fraction of accident costs) are externalities, so insurers would receive just a portion of the benefits, while incurring the full transaction and monitoring costs. Benefits to the insurance industry may not outweigh additional costs (Wenzel, 1995; Victoria Transport Policy Institute, 2011). Bordoff and Noel (2008) estimate the benefits to insurance companies at $34 per year per vehicle switching from traditional rating to PAYD, while the social benefit is estimated at $257 per car.

Some insurers offer PAYD pricing based on self-reported mileage. At renewal time, policyholders must provide their odometer reading, sometimes supplemented by a digital photograph of the odometer. The insurer performs random checks to monitor accuracy. Alternatively, odometer audits are performed by certified businesses, upon insurance renewal or upon mandatory inspections. Such policies are not likely to survive the current drastic price reductions of telematics devices, as they suffer from numerous disadvantages. There is a clear conflict of interest for the consumer which makes the system unreliable; the consumer has an incentive to report an understated mileage figure, hoping that he will not be selected for spot-checking; any random check is bound to occur several weeks after mileage reporting, giving the driver plenty of time to invent an excuse to explain the discrepancy, such as an unexpected recent trip; the consumer could even photograph another odometer. Non-digital odometers can be tampered. Odometer accuracy is affected by factors such as tire size, wear and tear. Mileage self-reporting disregards additional behavior data such as night driving, unsafe speeds, and hard brakes. There is no opportunity to generate additional revenue through the sale of ancillary services (Ptolemus Consulting Group, 2012; Victoria Transport Policy Institute, 2011). So it is likely that self-reported mileage is on its way out, due to the unreliability of mileage statements and the rapid price decrease of computer-based devices.

The advantages of telematics-based mileage pricing are substantial:

* Mileage pricing is more accurate, as it depends on individuals' own behavior and is directly based on exposure to risk, and not on the behavior of groups of people such as single males or inhabitants of a given township. PAYD improves fairness, by shifting weight in pricing towards an individually controllable factor, rather than based on involuntary membership in a group. Drivers have more control over their own premium. Pricing does not rely on variables such as gender, age, and territory, that can become unlawful.

* Subsidies across groups are decreased: safe, low-mileage drivers do not have to subsidize high-mileage road warriors.

* Uninsured driving may reduce. In some jurisdictions, a significant proportion of vehicles is uninsured because of high-premium costs. Mileage-pricing would make insurance for low-mileage cars more affordable, which can help reduce the uninsured problem. All policyholders would benefit, as the cost of uninsured and underinsured motorist coverage would decrease.

* Fraud opportunities are greatly reduced. Any resulting decrease in insurance premium leakage can be returned to policyholders in the form of premium cuts.

* If factors like excessive speeds and hard braking are taken into account, drivers have a strong incentive to improve driving skills and drive more carefully.

* Traditional pricing does not present drivers with a marginal insurance cost per mile driven. With PAYD, consumers have an incentive to drive less, leading to lower accident risks.

* Since PAYD gives consumers an incentive to reduce their insurance costs, it is likely that PAYD will have the external benefit of reducing total national mileage driven. Reduced driving has a positive effect on the environment (CO_2 and other air pollutants emissions, noise, traffic congestion). It reduces time wasted in traffic jams, fuel consumption, and helps nations move towards energy independence. It

decreases accident probabilities not only for the policyholder, but also for other road users. Indeed, a fall in mileage clears traffic from roads and reduces the likelihood of accidents for everyone (including non-drivers). Accident savings accrue to all other drivers and their insurance companies when any one driver forgoes a mile – obviously when a driver is off the road, no one has a chance of being involved in an accident with him. This is called accident externality. Bordoff and Noel (2008), using aggregate data, estimate externality savings in the US averaging 2.4 cents per mile, with wide variations across states due to traffic density – up to 54 cents per mile in Hawaii, the most congested state. Huang, Tzeng, and Wang (2012), using individual rather than aggregate data, obtain a much higher average externality cost of 13 cents per kilometer in Taiwan, probably due to the high traffic density in that country.

Using an elasticity of miles driven with respect to the marginal per mile price of -0.15, Ferreira and Minikel (2010) estimate that per mile auto insurance pricing would reduce mileage, accident costs, and fuel consumption by 9.5%. Edlin (2003) estimates mileage savings at 10%, Bordoff and Noel (2008) at 8%, equivalent to the savings that would result from a $1 per gallon tax increase.

* In the case of monthly premiums, the delay between improved driving and premium discount is reduced. With traditional pricing, claim-free driving is rewarded by a bonus-malus discount only at the next annual premium renewal. With monthly reporting of driving behavior and mileage, policyholders get frequent signaling, prudent driving is rewarded faster. With the consequences of each mile driven in mind, mileage-based insurance may have an immediate impact on the decision to start a particular trip.

* Telematics devices can provide numerous side benefits, such as:

- Automatic crash assistance. Medical services can be alerted immediately by the monitoring service, even if the driver is unconscious. This may possibly increase survival probabilities, and reduce medical costs.

- Roadside assistance. The monitoring service can provide real-time information about traffic problems, call assistance in case of a technical problem, even open car doors remotely if the key has been forgotten inside the car.

- Stolen car recovery. The continuous emission of a signal by the transmitter greatly improves the chances of a stolen car being recovered by police rapidly.

- Production of a detailed logbook of daily distances covered for tax purposes.

However, telematics pricing has several important disadvantages:

- Installation and monitoring costs can be substantial for some categories of drivers.

- Premiums, depending on variable mileage, become less predictable for drivers and insurers.

- Telematics mileage monitoring is currently nearly exclusively used to provide discounts to policyholders; premium increases are rare, and often not approved by regulators. This results in an overall reduction of premium income for the insurance industry, which may - or may not - be compensated by a decrease in traffic crashes and costs. Insurers may suffer a loss if crash costs decrease less than premium income. Reduced premiums also mean reduced investment income and brokers commissions.

- If a large proportion of policyholders switch to PAYD and get discounts, the insurer will be forced to increase premiums for drivers keeping traditional rating (if approved by regulators). This may create a "death spiral" of a dwindling number of insureds paying ever-increasing premiums. This may create some unrest, if these insureds mostly belong to socially disadvantaged groups.

- Distance-based pricing is currently exclusively offered as an option. This could create adverse selection, with policyholders driving less than average selecting PAYD to receive a discount, and high-mileage consumers sticking to car-year pricing. PAYD will attract drivers with high per-mile claim costs – urban drivers for instance. If all consumers continue to drive the same amount of miles, insurance premium income will decrease, with claim costs remaining at their current level. Evidence of adverse selection was confirmed by Muermann and Kremslehner (2012) using European telematics data. The number of car rides (controlling for mileage), speeding above limits, and relative distance driven on week-ends, were found to have significant impact on contract selection and risk.

- Motorists in multi-vehicle households could game the system by shifting driving from mileage-priced cars to cars with fixed-rate premiums.

- Customer tracking can be perceived as intrusive, and as an invasion of privacy. Customers may be leery of allowing their insurance company to track their location and driving hours.

- Practical and legal issues are bound to occur. Exact mileage to be driven is uncertain at the beginning of the year. As insurance premiums are always paid anticipatively, customers in practice would have to pre-pay for the miles they expect to drive. A premium adjustment would then take place during, or at the end of the policy-year, in the form of a refund, a carry-over to next policy year, or an additional payment. Policyholders cannot be expected to voluntarily self-report excess mileage; regulators will require the insurer to notice the excess and bill the policyholder accordingly, resulting in additional costs. What if a claim occurs after the pre-paid number of miles has been exceeded? Any position taken by the insurance industry than the claim is not covered, or that the company has the right to recover the cost from the policyholder, is certainly going to be challenged in court, with the insurer most likely to lose the case.

- The development of PAYD may be hampered by regulations, and by patents held by companies producing transmitters. Many US states prohibit retrospective rating – which would be a feature of PAYD for drivers who exceed their estimated pre-paid mileage.

4. The Data

4.1. Background

Taiwan has a land area of 32,260 sq. km, the size of Belgium, and a population of 23,113,900 in July 2012 (CIA, 2012). Two thirds of the state consist mostly of rugged mountains, leading to a very high population density in the plains. This density, along with the unavailability of parking in cities and the excellent public transportation network, results in a number of private cars that is low for an affluent country. Only 4,675,000 non-commercial sedans were registered in 2010, for a state that has a GPD per capita (corrected for purchasing power) of $37,000, identical to Germany (Taiwan Insurance Institute, 2012). Very few couples own two cars. It is rare for young individuals to own a car, due to high cost and taxes. Due to the presence of over 6.5 million motorcycles, traffic density is high – a further deterrent to multi-car ownership.

Automobile insurance is organized in a somewhat different way than in most western countries. Compulsory liability only covers bodily injury losses up to a limit that currently stands at NT$2,200,000 per person (1 NT$ = US$ 29.994 as of August 2012). The small increase of the limit during our observation period, from NT$1,600,000 to NT$1,700,000, is not expected to impact our study, as the vast majority of policyholders purchase coverage above the limit. Voluntary policies provide additional third party bodily injury and property damage coverage. Our data pools all of these policies, that are subject to the same rating variables and bonus-malus system. First party collision coverage is also available, but not considered in this study, as subject to another bonus-malus system.

Only three *a priori* classification variables are used by Taiwanese insurers for rating purposes: use of car (personal / business), gender (male / female) and driver age (< 20, 20-25, 25-30, 30-60, >60). As females receive a discount, a fact well known to Taiwanese households, it is a common practice for couples to register their car to the female driver. As a result, while the vast majority of drivers on the road are males, insurers report 70% of female drivers in their portfolios!

The bonus-malus system (BMS) has no upper limit in the malus zone. However, no single driver in our sample pays more than a 60% surcharge. Therefore, we can model the Taiwanese bonus-malus system as a 10-class Markov Chain, with premiums levels 70, 80, 90, 100, 110, 120, 130, 140, 150, and 160. New drivers start in class 4, at level 100. Claim-free years are rewarded by a one-class discount, leading to a 10% premium reduction. Each claim is penalized by three classes, or 30% of the basic premium.

4.2. Data

Our data result from the pooling of claim and policy information from the largest auto insurer operating in Taiwan (with a market share of 20%) with maintenance records from a chain of repair shops operated by the largest car manufacturer in the country (market share: 38%). Besides claim records, insurance variables include the gender, age, and marital status of the main driver, territory, use of car, bonus-malus class, and cubic capacity of the engine. As odometer readings are systematically collected by repair shops during each visit, interpolation or extrapolation of odometer values between visits allows us to estimate annual mileage. Data are available for seven policy years, 2001 to 2007. All policyholders purchased the compulsory policy; 88.82% bought additional voluntary insurance.

All claims, whether reported under the compulsory contract or one of the voluntary policies, are recorded. A claim may trigger a payment under a compulsory and/or a voluntary policy. To avoid double counting, claims reported on the same date under two or three policies are counted as a single claim. Unavoidably, some claims may be missed, for instance a property damage only claim, if the driver did not purchase the corresponding voluntary coverage – not a likely occurrence since nearly 89% of drivers in our sample purchase voluntary coverage. However, this may raise a potential problem, if high-mileage users are more prone to purchase additional insurance. If this is the case, more claims will be missed among the low-mileage drivers, and the impact of mileage on claim frequencies may be somewhat overstated. Such a behavior is well-known in collision coverage, but fortunately, does not take place in our third-party sample, as shown in table 1. (Policies are ranked by increasing mileage, and subdivided into ten equal-sized classes. "40-50", for instance, groups all policies with mileage comprised between the 40th and 50th percentile).

Mileage class	<10%	10-20	20-30	30-40	40-50	50-60	60-70	70-80	80-90	>90%
% voluntary	87.86	87.94	88.16	89.08	89.38	88.93	89.02	89.14	89.62	89.12

Table 1: Percentage of drivers purchasing voluntary coverage according to mileage class.

Our database is very large: over a quarter million policy-years, with a large set of different car models. Still, it only represents about 0.8% of the Taiwanese auto insurance market. Our sample may not be fully representative of the entire market, as it consists exclusively of drivers who (i) purchased a car from a particular brand; and (ii) use the dealer repair shops for maintenance. In Taiwan as in western countries, maintenance and repairs performed by dealers are somewhat more expensive; the network of dealer repair shops is not very dense, so using the services of these shops may require more driving time. Also, the waiting time at these shops may be longer than in specialized maintenance shops who perform basic services in a matter of minutes. Therefore, our sample may be somewhat selected in the sense that it consists of car owners who feel highly responsible for their car maintenance – which may correlate with a more responsible driving behavior. These owners are more likely to be affluent, married, middle-age or old, all factors linked to a lower claim frequency (Bair *et al*, 2012).

On the other hand, our sample drivers probably have a much higher annual mileage than average. The average mileage in our sample is 16,167 km, a surprisingly high figure for a small country, higher than in the USA or Western Europe. High users drive newer cars and maintain them well; older cars are more often maintained in small shops – besides the obvious remark that cars can only be owned very long if the annual mileage is low. Also, very low mileage cars are excluded from the sample, as they do not have the two repair shop visits that are needed to extrapolate mileage. This could result in our sample drivers having a higher claim frequency.

4.3. Variables

For all policyholders in our sample, the values of the following variables are recorded.

<u>Gender</u> Gender is a classification variable used in rating. Only 29.49% of policies are registered as males, a clear indication that policyholders take advantage of their knowledge of differential rates to get a premium discount. So it is all but certain that policies registered in the "female driver" category

include a large number of cars owned by couples, often driven by males. Repair shops report that over 80% of their customers are males.

<u>Age</u> Age is also used in rating. While for rating purposes the company uses five age categories (< 20, 20-25, 25-30, 30-60, >60), less than 1% of drivers are between ages 20 and 25, and only a handful are between 18 (the minimum driving age) and 20. Consequently, we combined the first three age categories and ended up with three classes: under 30 (7.38% of drivers), 30-60 (88.76%), over 60 (3.86%). The large percentage of middle-age policy owners may also reflect some selection by policyholders. As middle-age drivers pay a lower premium than the other groups, families have an incentive to register their car under the name of a 30-60 year old family member, preferably female.

<u>Vehicle type and use</u> 97.9% of cars are registered as non-commercial use sedans. Hence we discarded the remaining categories (business use, trucks, passenger coaches, taxis, *etc*).

<u>Mileage</u> Mileage is expressed in kilometers driven per day. Repair shop technicians note date and odometer reading on each visit of the car to the shop. If two or more visits are recorded, extrapolation or interpolation then yields the annual mileage. As an example of mileage calculation (Huang *et al*, 20xx), assume a driver has three visits to the repair shop. His odometer readings are 13,200 on October 1, 2001, 24,400 on April 1, 2002 (182 days later, 91 days into 2002, 274 days before January 1, 2003, and 37,400 on January 15, 2003 (289 days later, 15 days into 2003). The estimate of the number of kilometers driven in 2002 is

$$(24{,}400-13{,}200) \times (91/182) + (37{,}400-24{,}400) \times (274/289) = 17{,}925$$

A visual inspection of the data shows numerous instances of obvious recording mistakes, with mileages like -44,581 km or +24,833 km. Truncating the upper and lower 1% of the data seems a conservative approach, eliminating all unrealistic figures. The truncation daily mileage varies across policy years, averaging 7.43 km and 133.37 km. The remaining 98% of policies are then subdivided in ten deciles. Average class limits are provided in table 2. For instance, the third mileage class includes all cars driven between 25.24 and 30.44 km per day, from the 20^{th} to the 30^{th} percentile.

Mileage deciles	10%	20%	30%	40%	50%	60%	70%	80%	90%
Average class limit	19.02	25.24	30.44	35.27	40.32	46.13	54.73	62.22	76.42

Table 2: Average limits for the ten mileage classes, in km per day.

After elimination of business users, trucks, and the unreasonable mileage figures, the total sample size is 259,065. The average annual number of kilometers driven per car in our sample is 16,167.

Several variables are recorded by the company for classification purposes. They include:

<u>Marital status</u> 92.03% of policy owners are married – probably a higher percentage than in the overall insured population, due to selection.

<u>Car age</u> 26.45% of cars in the sample are under one year of age. 26.19% are between ages 1 and 2, 18.4% between ages 2 and 3, 12.38% between ages 3 and 4, 8.05% between ages 4 and 5, 8.53% are

older. Newer cars are possibly over-represented in our sample, as owners of new cars tend to follow maintenance guidelines more strictly; owners of older cars may look for cheaper shops for repairs and maintenance, or perform basic maintenance on their own. On the other hand, as the car manufacturer recommends maintenance every 10,000 km, low-mileage drivers may not visit the repair shop twice in their first driving year; as a minimum of two visits are required to extrapolate annual mileage, this may result in an under-representation of brand-new cars in our sample.

<u>City</u> 49.99% of our sample drivers live in an urban area.

<u>Territory</u> 47.45% of cars are registered in the north of Taiwan, 30.16% in the south, 17.31% in central Taiwan, and 5.08% in the eastern part of the island.

<u>Cubic capacity of engine</u> The engine capacity is under 1,800 cc for 65.80% of cars, between 1,800 and 2,000 for 28.92% of cars, and above 2,000 cc for the remaining 5.28%.

4.4. Claim Frequencies

Table 3 provides claim frequencies (= average number of claims per policy-year) for all classes of the rating variables age and gender.

Age group	Males	Females	All
< 30	0.0674	0.0652	0.0661
30 – 60	0.0473	0.0562	0.0537
> 60	0.0477	0.0523	0.0500
All	0.0493	0.0567	0.0545

Table 3: Claim frequencies for rating variables

The overall claim frequency (0.0545) in our sample is substantially larger than the frequency of 0.0343 observed in the entire portfolio of our insurer, for over 4.5 million policy-years. There is thus a substantial selection effect in our sample, despite the fact that the drivers in our database are likely more responsible than average. This seems to validate our conjecture that our sample consist of high-mileage drivers.

Surprisingly, the average claim frequency is higher for females (0.0567) than males (0.0493). Yet, females are the ones getting a discount. This surprising result is not specific to our sample, as it is also observed in the entire 4.5 million policies of the insurance company (male claim frequency: 0.0299; female: 0.0403). Possible explanations for this result include:

1. The main difference between male and female drivers lies in claim severity: males have significantly more costly accidents – and this justifies the male surcharge.
2. This confirms that the “female” group mostly consists of couples, with the male doing most of the driving for cultural reasons. “Female” – rated policies are for the most part driven by males. Couples are likelier to drive more that singles.
3. Note that differentiated mileage across “males” and “females” is not an explanation, as the average daily numbers of kilometers for males (46.38) and females (43.42) are hardly different.

Table 4 and Figure 1 provide claim frequencies as a function of mileage. Table 4 also presents variances of claim distributions.

Mileage deciles	Average mid-point (km)	Claim frequency	Variance
1	13.23	0.0351	0.0497
2	22.13	0.0344	0.0480
3	27.84	0.0434	0.0610
4	32.86	0.0470	0.0645
5	37.80	0.0511	0.0717
6	43.23	0.0554	0.0770
7	50.43	0.0593	0.0828
8	58.47	0.0632	0.0884
9	69.32	0.0721	0.1005
10	104.90	0.0838	0.1211

Table 4: Mean and variance of claim count distribution for ten mileage classes

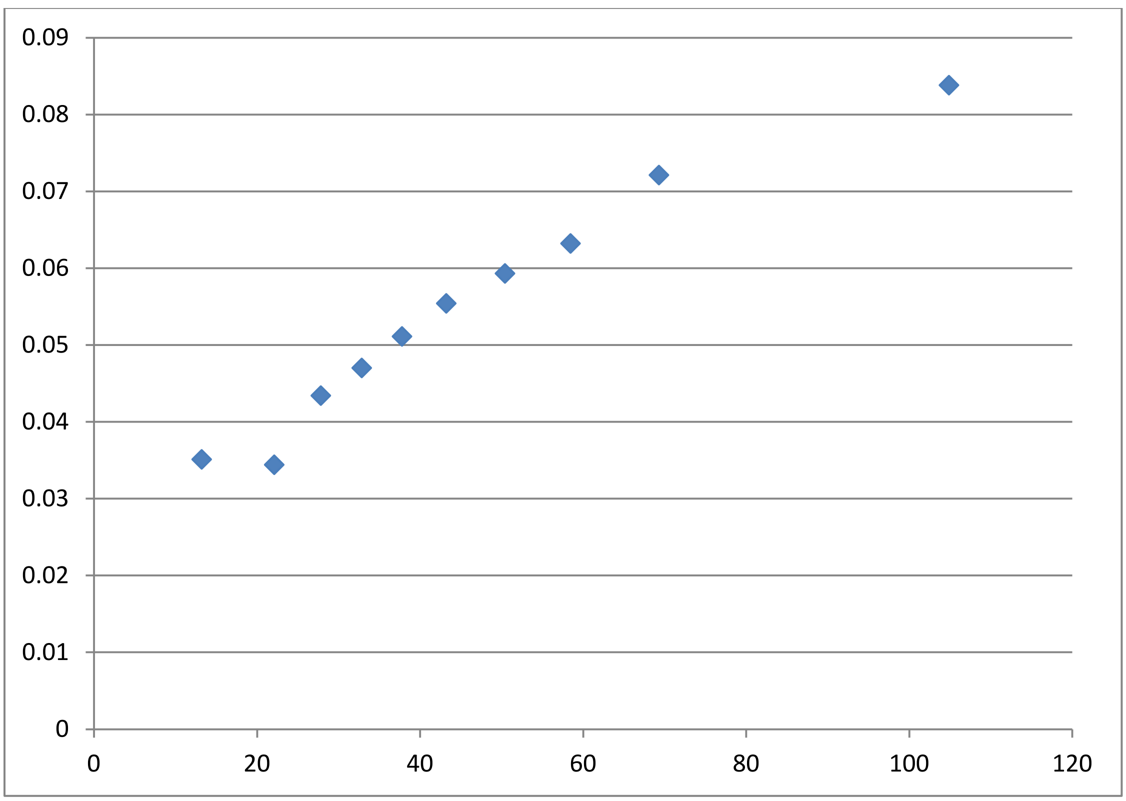

Figure 1: Claim frequency as a function of daily number of kilometers

As shown in all previous studies, claim frequencies increase with mileage, but in a less-than-proportional way.

5. Regressions

In this section, the following probit and ordered probit regression models analyze the importance of annual mileage, as compared to other classification variables.

$$\text{Probit}\ (C_{it}) = \alpha + \beta_1 X_{it} + \beta_2 Y_{it} + \beta_3 BMS_{it} + \beta_4 Mileage_{it} + \beta_5 D_t + \varepsilon_{it}$$

where, in the probit model, C_{it} is a dummy variable taking the value 1 if policyholder i had a claim in year t, and 0 if he did not. In the ordered probit model, C_{it} is the number of claims for policyholder i in year t. X_{it} is an array of rating variables (gender and age) that vary with individual and time. Y_{it} is an array of possible other classification variables (marital status, car age, city, territory, engine cubic capacity). BMS_{it} is the bonus-malus coefficient. $Mileage_{it}$ is the actual mileage recorded for driver i in year t. D_t is a set of annual dummy variables used to control year effects. β_1, β_2, β_3, β_4, and β_5 are coefficients corresponding to these variables. ε_{it} is the error term for individual i in year t.

The main variable of interest is annual mileage. Its coefficient β_4 will be positive and significant if, as expected, mileage driven is an important risk factor for the number of claims. The coefficient of BMS β_3 is also expected to be significantly positive, as a higher BMS class implies higher risk. The significance of this a *posteriori* variable may change once annual mileage and all other *a priori* classification variables are included in the regression model, if BMS captures residual risk differences undetected by the current rating factors.

Tables 5 and 6 present summary statistics and correlation coefficients for all variables.

Variable	Mean	Std Dev
Age<30	0.0738	0.2614
Age30-60	0.8876	0.3158
Age60+	0.0386	0.1927
Female	0.7051	0.4556
Married	0.9203	0.2708
Car age0	0.2645	0.4411
Car age1	0.2619	0.4397
Car age2	0.1840	0.3875
Car age3	0.1238	0.3294
Car age4	0.0805	0.2720
Capacity 2	0.2892	0.4534
Capacity 3	0.0528	0.2237
City	0.4999	0.5
North	0.4745	0.4994
South	0.3016	0.4590
Middle	0.1731	0.3784
BMS	0.8180	0.1332
Mileage	44.29	22.69

Number of observations: 259,065

Table 5: Summary Statistics

	Age<30	Age3060	Age60+	Female	Married	Carage 0	Carage 1	Carage 2	Carage 3	Carage 4	capacity 2	capacity 3	City	North	South	Middle	BMS	Mileage
Age<30	1	-0.793 <.0001	-0.056 <.0001	-0.062 <.0001	-0.263 <.0001	0.043 <.0001	0.026 <.0001	-0.004 0.0301	-0.021 <.0001	-0.031 <.0001	-0.061 <.0001	-0.040 <.0001	-0.027 <.0001	-0.009 <.0001	-0.009 <.0001	0.022 <.0001	0.093 <.0001	0.0553 <.0001
Age3060		1	-0.563 <.0001	0.108 <.0001	0.194 <.0001	-0.012 <.0001	-0.006 0.0015	0.001 0.3502	0.010 <.0001	0.009 <.0001	0.050 <.0001	0.022 <.0001	0.022 <.0001	0.005 0.0095	0.013 <.0001	-0.017 <.0001	-0.044 <.0001	-0.012 <.0001
Age60+			1	-0.093 <.0001	0.038 <.0001	-0.039 <.0001	-0.026 <.0001	0.002 0.1584	0.013 <.0001	0.026 <.0001	0.0013 0.4879	0.017 <.0001	0.000 0.8504	0.004 0.0339	-0.009 <.0001	-0.002 0.2576	-0.053 <.0001	-0.054 <.0001
Female				1	0.063 <.0001	0.031 <.0001	0.007 <.0001	-0.004 0.0133	-0.010 <.0001	-0.017 <.0001	-0.074 <.0001	-0.063 <.0001	-0.039 <.0001	-0.092 <.0001	0.060 <.0001	0.041 <.0001	0.036 <.0001	-0.052 <.0001
Married					1	0.009 <.0001	0.0042 0.0327	-0.003 0.0825	-0.006 0.0007	-0.002 0.1542	0.0440 <.0001	0.0335 <.0001	-0.016 <.0001	0.005 0.0037	-0.022 <.0001	0.009 <.0001	0.003 0.0605	-0.012 <.0001
Carage0						1	-0.357 <.0001	-0.284 <.0001	-0.225 <.0001	-0.177 <.0001	0.014 <.0001	-0.027 <.0001	-0.064 <.0001	-0.101 <.0001	0.061 <.0001	0.045 <.0001	0.697 <.0001	0.014 <.0001
Carage1							1	-0.282 <.0001	-0.223 <.0001	-0.176 <.0001	0.027 <.0001	-0.015 <.0001	0.014 <.0001	0.042 <.0001	-0.029 <.0001	-0.016 <.0001	0.0155 <.0001	0.02 <.0001
Carage2								1	-0.178 <.0001	-0.140 <.0001	0.0110 <.0001	0.001 0.5051	0.021 <.0001	0.033 <.0001	-0.021 <.0001	-0.012 <.0001	-0.247 <.0001	-0.006 0.0014
Carage3									1	-0.111 <.0001	-0.013 <.0001	0.010 <.0001	0.019 <.0001	0.025 <.0001	-0.015 <.0001	-0.011 <.0001	-0.275 <.0001	-0.008 <.0001
Carage4										1	-0.018 <.0001	0.019 <.0001	0.015 <.0001	0.014 <.0001	-0.006 0.002	-0.009 <.0001	-0.226 <.0001	-0.014 <.0001
Capacity 2											1	-0.15 <.0001	0.05 <.0001	0.041 <.0001	-0.018 <.0001	-0.025 <.0001	-0.025 <.0001	0.061 <.0001
Capacity 3												1	0.026 <.0001	0.015 <.0001	-0.024 <.0001	0.009 <.0001	-0.016 <.0001	0.006 0.0021
City													1	0.152 <.0001	-0.142 <.0001	0.106 <.0001	-0.062 <.0001	-0.118 <.0001
North														1	-0.624 <.0001	-0.434 <.0001	-0.091 <.0001	-0.015 <.0001
South															1	-0.300 <.0001	0.059 <.0001	0.027 <.0001
Middle																1	0.036 <.0001	-0.029 <.0001
BMS																	1	0.027 <.0001
Mileage																		1

Table 6. Correlations

Table 7 shows the result of probit models regression analyses. Results from the ordered probit models are almost identical to the probit models. They are presented in Appendix I. Model (1) includes all current rating variables together with BMS. All variables are significant at the 1% level. Surprisingly, the sign of the female variable is positive, which is counter-intuitive; the signs of all other variables are as expected. Female drivers get a discount, in Taiwan as most other countries, but regression results suggest that females report more claims than male drivers, supporting our conjecture that this variable is unreliable. Note the enormous significance of BMS – it is far more important than all other variables, as measured by the chi-square metric.

In model (2), the annual mileage variable is added, and found, as expected, to have a hugely significant positive effect: it has the largest chi-square of all variables, followed by BMS. The marginal effects of mileage at various points are presented in Figure 2 and Table 8. Figure 2 presents the increased claim probability when the mileage class is increased from i to i+1 in year 2007. The blue line shows the marginal effects at median values of all other variables; the red line shows the marginal effects for a high risk group (age <30, female, worst BMS class), and the green line for a low risk group (age 30-60, male, best BMS class). Figure 2 shows that the marginal effects are all positive: the claim probability increases with mileage driven. Interestingly, this probability increase is larger for high mileage drivers: the claim probability increases by 0.25% when the mileage class changes from 1 to 2, and by 0.49% when the mileage class changes from 9 to 10, for a median policyholder.

Variables	(1)	(2)	(3)	(4)
Age 30 – 60	-0.0745*** 21.71 (<0.0001)	-0.0546*** 11.53 (0.0007)	-0.0595*** 12.67 (0.0004)	-0.0372*** 4.91 (0.0267)
Age 60+	-0.0905*** 10.52 (0.0012)	-0.0372 1.75 (0.1858)	-0.0696** 5.97 (0.0146)	-0.0126 0.19 (0.6609)
Female	0.0575*** 33.91 (<0.0001)	0.0738*** 55.13 (<0.0001)	0.0470*** 22.05 (<0.0001)	0.0633*** 39.56 (<0.0001)
Bonus-Malus	0.6011*** 286.41 (<0.0001)	0.5749*** 259.22 (<0.0001)	0.1711*** 9.74 (0.0018)	0.1470*** 7.18 (0.0074)
Mileage		0.0427*** 750.29 (<0.0001)		0.0439*** 778.15 (<0.0001)
Married			-0.0326** 3.87 (0.0491)	-0.0347** 4.34 (0.0371)
Car age 0-1			0.1804*** 64.31 (<0.0001)	0.1798*** 63.36 (<0.0001)
Car age 1-2			0.0722*** 13.48 (0.0002)	0.0647*** 10.71 (0.0011)
Car age 2-3			0.0152 0.57 (0.4495)	0.0104 0.26 (0.6079)
Car age 3-4			0.0244 1.31 (0.2528)	0.0203 0.8975 (0.3435)
Car age 4+			-0.0044 0.03 (0.8529)	-0.0057 0.06 (0.8093)
Engine capacity 2			-0.0535*** 27.73 (<0.0001)	-0.0731*** 50.90 (<0.0001)

Engine capacity 3			-0.0532** 6.58 (0.0103)	-0.0675*** 10.46 (0.0012)
City			-0.0037 0.16 (0.6884)	0.0253** 7.34 (0.0067)
North			-0.0710*** 12.01 (0.0005)	-0.0702*** 11.61 (0.0007)
South			-0.0381 3.42 (0.0645)	-0.0404 3.82 (0.0505)
Middle			-0.0230 1.09 (0.2972)	-0.0191 0.74 (0.3894)
AIC	91047.101	90287.378	90893.924	90106.221
Likelihood Ratio	476.1761	1237.8987	653.353	1443.056
Number of Obs.	259,065	259,065	259,065	259,065

Three figures are provided in each cell. The above number is the regression coefficient. Below is the value of the Wald Chi-square and, between parentheses, the probability to exceed the Chi-square value. (p-value). *** indicates significance at the 1% level, ** at the 5% level. Annual dummy variables are included in all regressions, but not reported. They are all insignificant in the four selected models. For AIC (Likelihood Ratio), smaller (larger) value means better fit.

Table 7: Probit regressions

We expect the effect of mileage on claims to be larger for high risk groups than low risk groups; as a policyholder drives more, the chance of accident should increase more if the driver is high risk. This conjecture is tested by examining marginal effects at various points. Figure 2 shows that marginal effects for high risks are larger than for median and low risk groups in all mileage classes. Table 9 provides the claim probability increases, at various BMS coefficient levels, when the mileage class is changed from 1 to 10 for the three risk groups. As expected, Table 9 supports the conjecture that the claim probability increases more as high risks drives more. When the mileage class of a young male driver in the highest BMS class increases from 1 to 10, the probability of claim raises by 7.12%; for a male driver age 30 to 60 in the best BMS class, the change in claim probability is only 2.62%. Hence mileage is a more important variable for high risks; the impact of mileage is smaller for low risks. Therefore, if mileage is to be used as a rating variable, it is recommended to adapt a non-linear rating structure to reflect this difference. To check for the possibility that results may be influenced by the Normal link function used in Probit regressions, we also calculated marginal effects using Logit regression. Results provided in table 8 show that our results are very robust.

We conjectured that, possibly, the inclusion of mileage could reduce the explanatory power of BMS, if one of the residual risks captured by BMS is mileage driven. Results from models (1) and (2) suggest that this is not the case. The regression coefficient and chi-square values of BMS are only slightly reduced between model (1) and model (2), and BMS remains very significantly positive, implying that BMS contains important risk classification information unrelated to mileage. The inclusion of mileage reduces the chi-square value and the magnitude of Age 60+. The negative correlation between Age60+ and Mileage presented in Table 6 supports the interpretation that the annual mileage of elderly people tends to be very low, information that the Age60+ variable partially captures in the absence of mileage.

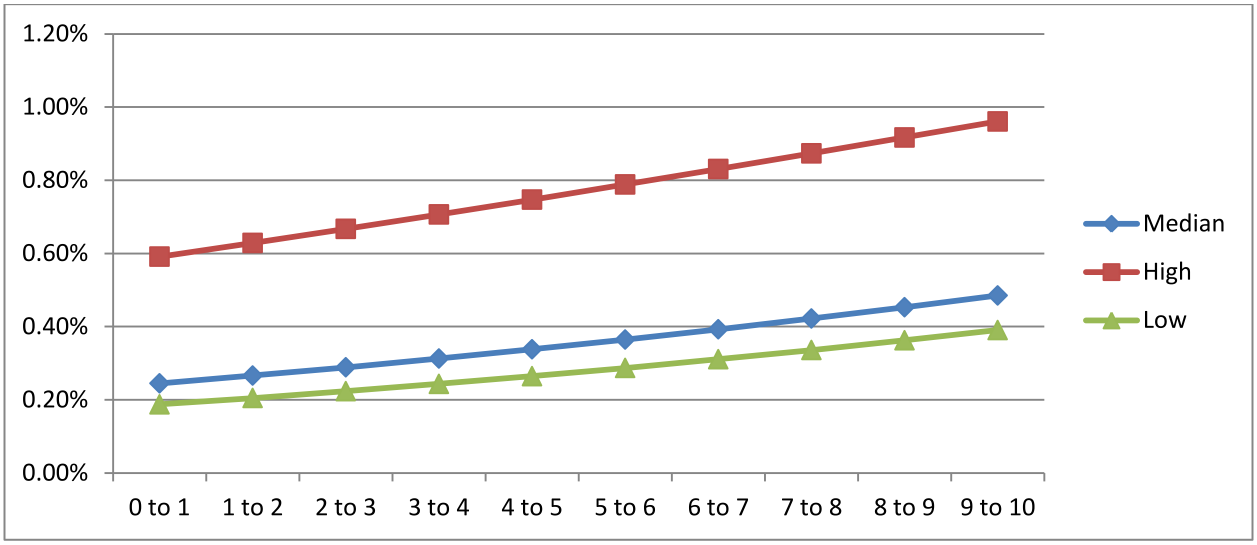

Figure 2: Marginal Effects of Mileage

Risk Group by Rating Variable	BMS coefficient	Marginal Effect (Probit)	Marginal Effect (Logit)
High: Age<30, Female	1.6	7.12%	8.58%
	1.5	6.62%	7.78%
	1.4	6.14%	7.04%
	1.3	5.68%	6.35%
Low: Age: 30 to 60, Male	1	3.57%	3.56%
	0.9	3.23%	3.18%
	0.8	2.92%	2.83%
	0.7	2.62%	2.52%

Table 8: Marginal Effects of Mileage

In models (3) and (4), all available classification variables are added. Mileage remains the most significant variable, as measured by the chi-square value, supporting the idea that annual mileage can be a very effective rating factor. Similar to the comparison of models (1) and (2), the inclusion of mileage variable does not affect the coefficient and the significance of BMS much. However, while BMS remains significant at the 1% level, its chi-square value is much reduced, from 286 to 9.4, by the inclusion of other classification variables, mostly car age, engine capacity, and territory. It seems that BMS acts as a substitute for risk information that could be captured by other observable variables.

The significant classification variables that could potentially be included in rating include car age, engine cubic capacity, and territory. The number of claims decreases with car age, whether or not mileage is included in the regression model. Car less than two years old have a highly significantly larger number of claims. Larger cars, with an engine cubic capacity exceeding 1,800 cc, are safer. Among territorial variables, only North has a significant effect, possibly due to the better quality of roads around the capital city of Taipei. While in most similar studies authors found that city drivers have more claims, this does not appear to be the case in Taiwan. This could be due to the fact that, in Taipei and other large cities, scooters have designated separate lanes, much reducing the probability of an impact with cars. These improved road designs have yet to be implemented in rural areas.

The conclusions of regression analyses are very strong. While we expected annual mileage to have a significant positive impact on claim frequencies, the very large chi-square values obtained for mileage, with and without other classification variables, indicate that, by far, mileage is the most accurate variable that insurers could introduce. The impact of mileage on claim frequencies surpasses the influence of all other variables, including BMS, by a wide margin. The significance of BMS, however, is not decreased by the inclusion of mileage. The Taiwanese BMS is fairly mild: penalties are not severe, when compared to BMs in force in most countries. Should Taiwanese companies decide to make transition rules and premium levels more severe, the significance of BMS would most probably increase. Introducing new variables such as car age, territory, and cubic capacity instead of a more severe BMS, while actuarially justified, would result in a complicated rating system with a large number of variables, that would be more difficult to understand by brokers and consumers. So bonus-malus systems should remain an important component of auto insurance rating.

6. Impact on Taiwanese Bonus-Malus System

The study of bonus-malus systems (BMS) became an important area of research in non-life actuarial science in the 1960s, jump-started by the first ASTIN Colloquium, held in La Baule in 1959 and devoted exclusively to the topic. Numerous authors designed tools to evaluate and compare existing BMS, and to design improved systems. This research is summarized in Lemaire (1995), among others. Noteworthy is the fact that BMS research developed independently of the study of other rating variables. Yet, authors appeared to be aware that the two subjects (*a priori* and *a posteriori* rating) should be connected. For instance, Lemaire and Zi (1994) observed that "The government may then seek to correct for the inadequacies of the *a priori* system by using a "tough" BMS" and "… the use of more *a priori* classification variables is expected in free market countries, which decreases the need for a sophisticated BMS" – but did not model this link in their research. Lemaire (1995) cites adverse selection and insurers' lack of knowledge of driving behavior of policyholders as one of the main reasons to introduce BMS, even mentioning annual mileage as main example.

Taylor (1997) was the first author to model explicitly the relation between BMS and other rating factors. He noted that failing to consider jointly *a priori* classification variables and BMS could lead to double-counting similar effects. For instance, young drivers are likely to be penalized by a high *a priori* surcharge, while gravitating to the malus zone of the BMS due to claims, thereby cumulating an explicit *a priori* penalty with an implicit BMS surcharge. For a given BMS with known number of classes and transition rules, Taylor developed a sophisticated Bayesian model, requiring extensive simulation, to calculate two sets of BMS premium levels: one that ignores correlations with *a priori* variables, and one that incorporates them. Through an example, Taylor showed that the range of BMS premium levels is reduced when covariates are taken into account. Unfortunately, Taylor could not access real-life data, and had to use an artificially-created example, using guesswork to select cell claim frequencies and variances, and a nine-class BMS that no insurance company uses in practice. Taylor assumed that, due to unspecified classification variables, policyholders can be subdivided in 10 risk groups, with mean group claim frequencies ranging from 6.5% to 50.5%, and fairly low within-group variation. With the premium level set at 100 for the starting class of the baseline BMS, simulated claim frequencies, uncorrected for rating variables, justify premium levels ranging from 55 to 150. Recognizing the impact of classification variables, premiums levels range from 73 to 123. In other words, accounting for the impact of covariates, the range of BMS premium levels can be reduced significantly: a much less severe BMS is needed to reflect varying driving behaviors.

The Taiwanese BMS and data provide us with a unique opportunity to implement Taylor's path-breaking work with real-life data, and to check whether the inclusion of annual mileage as an *a priori* rating variable would require a modification of the existing BMS.

Essential characteristics of the model are as follows (for theoretical developments, see Taylor, 1997). All policyholders are subdivided in ten mileage classes, as described in section 4.3. A classical negative binomial distribution is used in each class; the number of claims of each policyholder is assumed to be Poisson-distributed, with a parameter that varies according to a Gamma distribution. While Taylor used the moments method to estimate the parameters of each negative binomial distribution, two other estimation techniques are used here:

(i) The maximum likelihood method
(ii) Following a suggestion by Johnson *et al* (2005), a "Mean and P(0)" method that determines parameters by matching the observed and theoretical mean and the probability of no claim. This method appears efficient when a large proportion of insureds incurs no claim in a given year; it provides a slightly better fit than the maximum likelihood method, as measured by the χ^2 distance.

For the low claim frequencies observed in Taiwan, the BMS, described in section 4.1., appears to approach its stationary distribution after 50 to 60 years. Consequently, the portfolio is simulated for 60 years, and all percentages and ratios described below pertain to year 60. The simulation proceeds as follows:

(i) By design, each mileage class contains the same number of policies. Each driver is assigned to a mileage class with probability 1/10.
(ii) Each policy is assigned a Poisson parameter, by sampling from the Gamma distribution of the mileage class. The Poisson parameter does not change over time.
(iii) The driver's claims history is simulated for 60 years, tracking the evolution of the BMS level.

For maximum likelihood estimators, simulation results are summarized in tables 8 to 10. Similar tables for the "Mean and P(0)" method are presented in Appendix II. Table 8 presents the steady-state distribution of policyholders across mileage and BMS classes. Due to the low claim frequencies observed in Taiwan and the mild transition rules of the BMS (a three-class penalty per claim), a huge clustering of policies in class 1 takes place, with over 88% of policyholders eventually reaching this high-discount class. As expected, a selection effect according to mileage takes place, with more low-mileage users ending up in BMS class 1, and high-mileage users more likely to occupy BMS class 10, creating a potential "double-counting" effect if annual mileage is introduced as a rating variable without taking into consideration its effect on BMS premiums.

		Bonus-malus class									
		1	2	3	4	5	6	7	8	9	10
Mileage Class	1	.9320	.0091	.0099	.0124	.0048	.0058	.0059	.0063	.0099	.0148
	2	.9186	.0085	.0109	.0123	.0042	.0053	.0057	.0052	.0082	.0128
	3	.9082	.0083	.0118	.0142	.0070	.0083	.0080	.0071	.01228	.0193
	4	.8862	.0115	.0154	.0186	.0057	.0069	.0093	.0092	.0131	.0188
	5	.8927	.0135	.0158	.0168	.0075	.0090	.0065	.0107	.0128	.0223
	6	.8702	.0122	.0157	.0157	.0100	.0098	.0098	.0088	.0152	.0263
	7	.8782	.0126	.0158	.0174	.0082	.0088	.0117	.0104	.0135	.0241
	8	.8569	.0141	.0169	.0215	.0083	.0113	.0114	.0134	.0174	.0279
	9	.8510	.0157	.0181	.0253	.0077	.0113	.0112	.0121	.0201	.0320
	10	.8245	.0191	.0214	.0229	.0112	.0130	.0122	.0138	.0201	.0349
	All	.8819	.0125	.0152	.0177	.0075	.0090	.0092	.0097	.0142	.0233

Table 9: Stationary distribution of policyholders across mileage and bonus-malus classes, maximum likelihood estimators

Table 10 presents, for each BMS class,

(i) the steady-state population of each class
(ii) the "true claim frequency", or "raw claim frequency", which is the claim frequency effectively observed in each BMS, without taking into account annual mileage
(iii) the "cell claim frequency", or "expected claim frequency", which is the claim frequency expected in each BMS class using for each policyholder the claim frequency predicted by his mileage class – the average of his mileage class
(iv) the ratio "true/cell claim frequency" which measures the difference between actual and expected driving behavior based on mileage. The difference is due to the fact that, for instance, poor drivers have more accidents than the average of their mileage class. In essence, the impact of mileage is removed.

BMS level	% drivers	True claim frequency	Cell claim frequency	Ratio: true/cell
1	88.19%	1.43%	5.40%	26.40%
2	1.25%	12.36%	5.82%	212.36%
3	1.52%	11.47%	5.76%	199.13%
4	1.77%	16.54%	5.77%	286.73%
5	0.75%	20.78%	5.80%	358.23%
6	0.90%	27.60%	5.83%	473.38%
7	0.92%	35.01%	5.79%	604.58%
8	0.97%	41.13%	5.84%	704.35%
9	1.42%	51.58%	5.83%	884.79%
10	2.33%	72.77%	5.88%	1237.59%

Table 10: Steady-state distribution of policyholders, claim frequencies, maximum likelihood estimators.

Table 11 presents main results: the BMS levels as they are now, the BMS levels suggested by the simulation when the effect of covariates is ignored, and the BMS levels recognizing covariates. BMS levels ignoring covariates are obtained by standardizing true claim frequencies, setting the rate for starting class 4 at 100%. Suggested BMS levels are extremely low in class 1, and high in all malus classes. With overall claim frequencies in Taiwan very low, a large proportion of drivers practically never has an accident; these drivers rapidly end up in the best class, and, with few exceptions, stay there. Hence the observed claim frequency in class 1 is extremely low. On the other hand, given the large clustering of policies in the low BMS classes, classes 5 to 10 will be sparsely populated by poor drivers. Reaching class 10 requires multiple accidents, and a driving history that is rare in Taiwan. Consequently class 10 (and, to a lesser extent, classes 5 to 9) is occupied by the poorest drivers, who exhibit very high accident rates.

BMS level	Current BMS levels	BMS levels ignoring covariates	BMS levels recognizing covariates
1	70	8.62%	9.21%
2	80	74.71%	74.06%
3	90	69.33%	69.45%
4	100	100.00%	100.00%
5	110	125.59%	124.94%
6	120	166.81%	165.09%
7	130	211.59%	210.85%
8	140	248.63%	245.65%
9	150	311.79%	308.58%
10	160	439.85%	431.62%

Table 11: Current BMS levels, simulated BMS levels ignoring and recognizing covariates

Of course the design of a BMS needs to take into account many factors besides actuarial claim ratios, as BMS need to be accepted by management, regulators, customers. Regulators do not want a BMS so severe than it would promote hit-and-run behavior. Management also is not in favor of harsh penalties, as high malus premium level would encourage policyholders to leave the company, and try to get a fresh BMS start with another insurer, finding a strategy to "game" the system and by-pass information exchange across companies. So, a BMS with levels as high as suggested by the third column of table 10, while actuarially justified, would never be accepted by other stakeholders. Still, observed claim frequencies suggest that Taiwanese insurance companies have some room to make their BMS more severe.

BMS levels recognizing covariates are obtained by standardizing the "true/cell ratios" from table 9. They avoid double-counting by removing the mileage effect. Due to the low variability of claim frequencies across mileage classes, and the large concentration of policyholders in BMS class 1 independently of mileage, taking into account mileage differentials hardly modifies suggested BMS levels. This conclusion is very different from the results obtained by Taylor (1997), due to major differences in examples. Taylor considers ten rating classes, with claim frequencies ranging from 6.5% to 50.5%, and low variability within each class (coefficients of variation from 0.40 to 0.75). In Taiwan, the ten mileage-based rating classes have a much narrower range of claim frequencies, from 3.51% to 8.38%. Moreover, within-class variability is much higher, with coefficients of variations all in excess of 2.5. Consequently, while Taylor's ten distributions of Poisson parameters are well separated, ours overlap to a large extent, and recognizing covariates in BMS levels has a very limited impact. An attempt to subdivide the data in five mileage classes instead of ten to achieve more separation of distributions did not provide conclusive results.

The results from this section confirm conclusions from regression analyses. The interaction between mileage and BMS is small, so that the introduction of mileage in rating would not justify a significant weakening of the BMS premium levels. The "double-counting" effect is minimal. Mileage cannot "replace" BMS rating, cannot be used to reduce BMS discounts and penalties. Consequently, BMS should continue to play a major role in auto insurance rating in Taiwan.

7. Conclusions

In this research we have used the unique database of a major insurance carrier in Taiwan to investigate whether annual mileage should be introduced as a rating variable in auto third-party liability insurance. Admittedly, several characteristics of Taiwan and its insurance market are quite different from other countries: extreme traffic density, low number of cars given the high average wealth level, compulsory insurance that only requires bodily injury coverage with fairly low policy limits. However, our results are so strong that we can confidently extend them to all affluent countries. Annual mileage is an extremely powerful predictor of the number of claims at-fault. Its significance, as measured by Wald's chi-square and its associated p-value, by far exceed that of all other variables, including bonus-malus. This conclusion applies independently of all other variables possibly included in rating.

Insurance companies are at a crossroads. Several variables commonly used are being questioned by regulators. The E.U. now forbids the use of gender rating. Territory is being challenged as a substitute for race. Insurers are being pressured to find new variables, that predict accidents more accurately and are socially acceptable. Annual mileage seems an ideal candidate variable, to be introduced in rating whenever feasible. The recent development of GPS systems, on-board computers, and telematics devices, and the rapid decrease in price of the new technologies, should induce carriers to explore ways to minimize problems associated with Pay-As-You-Drive insurance.

The inclusion of annual mileage as a new rating variable should, however, not take place at the expense of bonus-malus systems. Bonus-malus systems are not a substitute for annual mileage, on the contrary the information contained in the bonus-malus premium level complements the value of annual mileage. An accurate rating system should therefore include annual mileage and bonus-malus as the two main building blocks, possibly supplemented by the use of other variables like age and territory.

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Appendix I: Regression results, Ordered Probit.

Variables	(1)	(2)	(3)	(4)
Age 30 – 60	-0.0735*** 21.61 (<0.0001)	-0.0539*** 11.50 (0.0007)	-0.0586*** 12.57 (0.0004)	-0.0366** 4.85 (0.0276)
Age 60+	-0.0822*** 8.94 (0.0028)	-0.0295 1.13 (0.2875)	-0.0614** 4.77 (0.0289)	-0.0048 0.03 (0.8641)
Female	0.0577*** 34.90 (<0.0001)	0.0739*** 56.48 (<0.0001)	0.0459*** 21.47 (<0.0001)	0.0621*** 38.82 (<0.0001)
Bonus-Malus	0.6183*** 311.39 (<0.0001)	0.5928*** 283.41 (<0.0001)	0.0541*** 10.93 (0.0009)	0.1546*** 8.16 (0.0043)
Mileage		0.0424*** 756.34 (<0.0001)		0.0436*** 783.32 (<0.0001)
Married			-0.0298 3.31 (0.0689)	-0.0320 3.76 (0.0524)
Car age 0-1			0.1856*** 69.69 (<0.0001)	0.1852*** 68.86 (<0.0001)
Car age 1-2			0.0724*** 13.86 (0.0002)	0.0650*** 11.06 (0.0009)
Car age 2-3			0.0198 0.99 (0.3198)	0.0150 0.56 (0.4526)
Car age 3-4			0.0272 1.65 (0.1986)	0.0232 1.19 (0.2751)
Car age 4+			-0.0033 0.02 (0.8883)	-0.0046 0.04 (0.8444)
Engine capacity 2			-0.0564*** 31.41 (<0.0001)	-0.0758*** 55.99 (<0.0001)
Engine capacity 3			-0.0606*** 8.61 (0.0033)	-0.0752*** 13.09 (0.0003)
City			-0.0073	0.0214**

			0.64 (0.4222)	5.37 (0.0204)
North			-0.0720*** 12.61 (0.0004)	-0.0713*** 12.26 (0.0005)
South			-0.0323 2.52 (0.1127)	-0.0347 2.89 (0.0890)
Middle			-0.0183 0.70 (0.4018)	-0.0146 0.44 (0.5053)
AIC	105105.62	104340.02	104932	104139.39
Likelihood Ratio	473.9446	1241.544	671.56	1466.1688
Number of Obs.	259065	259065	259065	259065

Three figures are provided in each cell. The above number is the regression coefficient. Below is the value of the Wald Chi-square and, between parentheses, the probability to exceed the Chi-square value (p-value). *** indicates significance at the 1% level, ** at the 5% level. Annual dummy variables are included in all regressions, but not reported. They are all insignificant in the four selected models. For AIC (Likelihood Ratio), smaller (larger) value means better fit.

Table A1 : Ordered Probit regressions

Appendix II: Bonus-Malus results for alternate parameter estimation technique: the "Mean and P(0) method.

Bonus-malus class

Mileage class	1	2	3	4	5	6	7	8	9	10
1	.9233	.0085	.0094	.0115	.0051	.0052	.0064	.0063	.0084	.0148
2	.9217	.0092	.0107	.0124	.0050	.0058	.0059	.0061	.0090	.0142
3	.9053	.0103	.0115	.0136	.0062	.0069	.0071	.0079	.0106	.0183
4	.8954	.0126	.0140	.0168	.0069	.0075	.0087	.0084	.0119	.0192
5	.8920	.0119	.0144	.0155	.0072	.0081	.0087	.0089	.0133	.0209
6	.8783	.0132	.0148	.0177	.0087	.0089	.0094	.0103	.0136	.0236
7	.8706	.0135	.0152	.0181	.0091	.0090	.0102	.0118	.0150	.0248
8	.8668	.0154	.0167	.0187	.0087	.0097	.0109	.0122	.0164	.0274
9	.8486	.0168	.0185	.0221	.0102	.0105	.0125	.0136	.0191	.0321
10	.8278	.0169	.0195	.0232	.0113	.0119	.0135	.0146	.0224	.0373
All	.8830	.0128	.0145	.0170	.0078	.0083	.0093	.0100	.0140	.0233

Table A2-1: Stationary distribution of policyholders across mileage and bonus-malus classes, "Mean and P(0)" estimators

BMS level	% drivers	True claim frequency	Cell claim frequency	Ratio: true/cell
1	88.30%	1.36%	5.40%	25.19%
2	1.28%	12.46%	5.76%	216.32%

3	1.45%	13.53%	5.76%	234.90%
4	1.70%	15.15%	5.76%	263.02%
5	0.78%	24.10%	5.83%	413.38%
6	0.83%	28.11%	5.80%	484.66%
7	0.93%	33.01%	5.83%	566.21%
8	1.00%	42.97%	5.86%	733.28%
9	1.40%	54.20%	5.90%	918.64%
10	2.33%	73.30%	5.90%	1242.37%

Table A2-2: Steady-state distribution of policyholders, claim frequencies, “Mean and P(0)” estimators.

BMS level	Current BMS levels	BMS levels ignoring covariates	BMS levels recognizing covariates
1	70	8.86%	9.50%
2	80	86.42%	88.56%
3	90	82.70%	83.28%
4	100	100.00%	100.00%
5	110	148.68%	146.90%
6	120	172.82%	173.42%
7	130	203.46%	202.06%
8	140	269.70%	264.67%
9	150	326.50%	324.81%
10	160	472.44%	462.85%

Table A2-3: Current BMS levels, simulated BMS levels ignoring and recognizing covariates, “Mean and P(0) estimators