TØI report 402/1998
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Summary:

Car ownership, road use, accidents, and injuries

A widened perspective on road accidents and safety

Road accidents occur as a result of a potentially very large number of (causal) factors exerting their influence at the same location and time. It might be fruitful to distinguish between six broad categories of factors influencing accident counts.

First, accident numbers depend on a number of truly *autonomous factors, determined outside the (national) social system*, such as the weather, the natural resources, the state of technology, the oil price, the population size and structure, etc – in short, factors that can hardly be influenced (except perhaps in the very long term) by any (single) government, no matter how strong the political commitment.

Second, they depend on a number of *general socio-economic conditions*, some of which are, in practice or in principle, subject to political intervention, although rarely with the explicit purpose of promoting road safety, nor – more generally – as an intended part of transportation policy (industrial development, (un)employment, disposable income, consumption, taxation, inflation, public education, etc).

At a third level, the size and structure of the *transportation sector*, and the policy directed towards it, obviously have a bearing on accident counts, although usually not intended as an element of road safety policy (transport infrastructure, public transportation level-of-service and fares, overall travel demand, modal choice, fuel and vehicle tax rates, size and structure of vehicle park, driver's license penetration rates, etc). Most importantly, many of these factors are strongly associated with aggregate *exposure*, i e with the total volume of activities exposing the members of society to road accident risk.

Fourth, the accident statistics depend, of course, on the system of *data collection*. Accident underreporting is the rule rather than the exception. Changes in the reporting routines are liable to produce fictitious changes in the accident counts.

Fifth, accidents counts, much like the throws of a die, are strongly influenced by sheer *randomness*, producing literally unexplainable variation. This source of variation is particularly prominent in small accident counts. For larger accident counts, the law of large numbers prevails, producing an astonishing degree of long-run stability, again in striking analogy with the dice game.

Finally, accident counts are susceptible to influence, and – indeed – influenced, by *accident countermeasures*, i e measures intended to reduce the risk of being involved or injured in a road accident, as reckoned per unit of exposure.

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Although generally at the center of attention among policy-makers and practitioners in the field of accident prevention, this last source of influence is far from being the only one, and may not even be the most important. To effectively combat road casualties at the societal level, it appears necessary to broaden the perspective on accident prevention, so as to – at the very least – incorporate *exposure* as an important intermediate variable for policy analysis and intervention.

TRULS – a member of the DRAG family of models

To understand the process generating accidents on Norwegian roads in such a widened perspective, we have set out to construct the model TRULS.

The TRULS model is a member of a larger family of model, all inspired by the DRAG model for Quebec, and explaining the Demand for Road use, Accidents and their Gravity, whence the acronym DRAG:

- DRAG (Demand Routière, les Accidents et leur Gravité), authored by Gaudry (1984) and further developed by Gaudry et al (1995), covering the state of Quebec.
- SNUS (Straßenverkehrs-Nachfrage, Unfälle und ihre Schwere), authored by Gaudry and Blum (1993), covering Germany.
- DRAG-Stockholm, authored by Tegnér and Loncar-Lucassi (1996), covering the Stockholm county of Sweden.
- TAG (Transports, Accidents, Gravité), authored by Jaeger and Lassarre (1997), covering France
- TRULS (TRafikk, ULykker og Skadegrad), the present author, covering Norway.

The common features of all members of the DRAG family is an at least *three-layer recursive structure of explanation*, involving road use, accident frequency, and severity, and an econometric technique – called *BC-GAUHESEQ* (*B*ox-*C*ox *G*eneralized *AU*toregressive *HE*eteroskesdastic *S*ingle *EQ*uation) – allowing for estimably non-linear relationships (Gaudry et al 1993, Liem et al 1993).

Road use (traffic volume) is not considered an exogeneous factors, but explained by a number of socio-economic, physical and political variables. *Accident frequency* is modeled depending on road use, the presumably single most important causal factor. *Accident severity* is modeled as the number of severe injuries or fatalities per accident, i e as the conditional probability of sustaining severe injury given that an accident takes place.

Thus, the total number of fatalities (e g) is decomposable into two parts: the number of accidents × the number of fatalities per accident. This multiplicative decomposition allows for added insights and interesting substantive interpretations, as we shall see later on.

The general structure of TRULS

Some DRAG-type models include additional layers of explanation or prediction. The TRULS model, e g, includes (i) *car ownership*, (ii) *seat belt use*, and (iii) a *decomposition between light and heavy vehicle road use*, adding to the set of econometric equations (see Fridstrøm 1998b).

Also, while most DRAG-type models use the fuel sales as a (rather imperfect) measure of the traffic volume, in TRULS we have constructed (iv) a *submodel designed to "purge" the fuel sales figures of most nuisance factors* affecting the number of vehicle kilometers done per unit of fuel sold (Fridstrøm 1998a). These nuisance factors include vehicle fuel economy, aggregate area-wide vehicle mix, weather conditions, and fuel hoarding due to certain calendar events or price fluctuations.

A further point at which the TRULS model differs from other members of the DRAG family, is by the estimation of (v) *separate equations for various subsets of casualties* (car occupants, seat belt non-users, pedestrians, heavy vehicle crashes, etc). These equations are meant to shed further light on the causal mechanism governing accidents and severity. In order to avoid, to the largest possible degree, spurious correlation and omitted variable biases, we develop certain *casualty subset tests* not previously used within the DRAG modeling framework.

Unlike other DRAG family models, the TRULS model departs from an assumption that casualty counts in general follow a (generalized) Poisson distribution (see Fridstrøm et al 1993, 1995). To enhance efficiency, in the accident equations we therefore rely (vi) on a *disturbance variance specification approximately consistent with the Poisson law*. To this end, we develop a special statistical procedure, termed Iterative Reweigted POisson-SKedastic Maximum Likelihood (IRPOSKML), for use within the general BC-GAUHESEQ statistical framework.

Finally, the TRULS model is the only DRAG-type model so far being based (vii) on *pooled cross-section/time-series data*. Other DRAG family models rely exclusively on time-series. Our data, however, are monthly observations pertaining to all counties (provinces) of Norway. The period of observation extends from January 1973 until December 1994, thus covering 264 months. Since there are 19 counties in the country, the data set contains a total number of 5 016 units of observation.

The structure and interdendencies between *endogenous* (*dependent*) variables in the TRULS model are shown in figure 1. In table 1 we provide an overview of (broad categories of) *independent* variables entering the model.

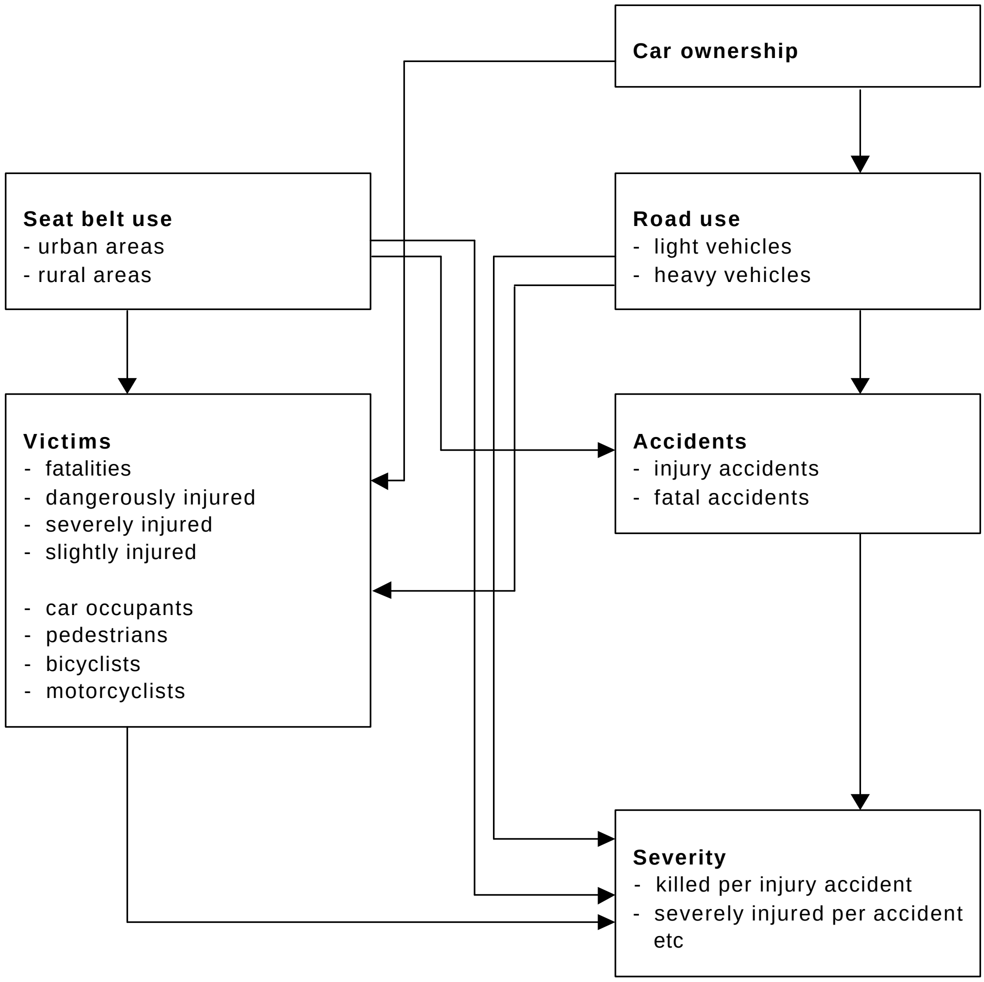

Figure 1: Dependent variables in the model TRULS

Table 1: Independent variables in the model TRULS

Independent variable	Direct effect upon					
	Car ownership	Vehicle kms	Seat belt use	Accidets	Victims	Severity
Infrastructure	√	√		√	√	√
Road maintenance				√	√	√
Public transportation	√	√		√	√	√
Population	√	√		√	√	√
Income	√	√				
Prices	√	√				
Interest rates	√					
Taxes	√	√				
Vehicle characteristics		√	√	√	√	√
Daylight		√		√	√	√
Weather conditions		√		√	√	√
Calendar effects		√		√	√	√
Geographic characteristics	√	√	√	√	√	√
Legislation			√	√	√	√
Fines and penalties			√			
Access to alcohol				√	√	√
Information		√	√			
Reporting routines				√	√	√
Randomness and measurement errors	√	√	√	√	√	√

Note that only *direct* effects are ticked off in this table. In general, the total effect of an independent variable on – say – accident frequency, will be a sum of direct and indirect effects, as channeled though the recursive system pictured in figure 1. For instance, the interest level has a direct effect on car ownership only. However, since car ownership affects road use, which in turn affects accidents, interest rates may turn out as an important *indirect* determinant of road casualties. The tracing of such effects is the very purpose of our multi-layer modeling approach.

Selected results from TRULS

As indicated by table 1, many of the same independent variables enter, respectively, the car ownership equation, the road use equation, the accident frequency equation, and the severity equations. At the same time, car ownership is an input in the road use equation, while road use is an input in the accident frequency and severity equations, forming a recursive chain of effects. To measure the total impact of a given independent variable, one has to add up the direct and indirect effects arising at the various steps. We do this by calculating and compounding the relevant partial elasticities (see Fridstrøm 1998c for a precise account of the method).

In figures 2 through 26 we show calculated elasticities with respect to various independent variables. The elasticities are computed for each sample point, and then averaged over all sample points observed in 1994 (19 provinces and 12 months). They include all direct and indirect effects, by recursive accumulation. That is, whenever applicable, the effect channeled through increased (or decreased) car ownership is included in the road use elasticity, the effect coming through increased road use is included in the accident elasticity, and the effect on accident frequency is included in the fatalities elasticity.

The values shown in figures 2-26 are point estimates. They should be interpreted with some caution, as the diagrams provide no information on standard errors or confidence intervals, or on whether the effects shown are significantly different from zero.

Exposure

In figure 2, we show estimated elasticities with respect to various components of exposure.

The injury accident frequency has an elasticity of 0.911 with respect to the total volume of motor vehicle road use (*vehicle kilometers*). That is, injury accidents increase almost in proportion to the traffic volume, *other things being equal*. Fatalities appear to increase somewhat less than proportionately, viz. by an elasticity of 0.761.

This elasticity applies, however, only on the condition that the *traffic density*, defined as vehicle kilometers driven per kilometer road length, is kept constant. In other words, the elasticities with respect to traffic volume implicitly assume that the road network is being extended at a rate corresponding exactly to the traffic growth, so that the ratio of vehicle kilometers to road kilometers remains unchanged.

In the opposite and more realistic case, where the road network does not change, an average accident elasticity of approximately 0.50 (= 0.911 - 0.414) is calculable for 1994. An increase in traffic density tends, in other words, to dampen the (otherwise near-proportionate) effect of larger traffic volumes, as measured in vehicle kilometers.

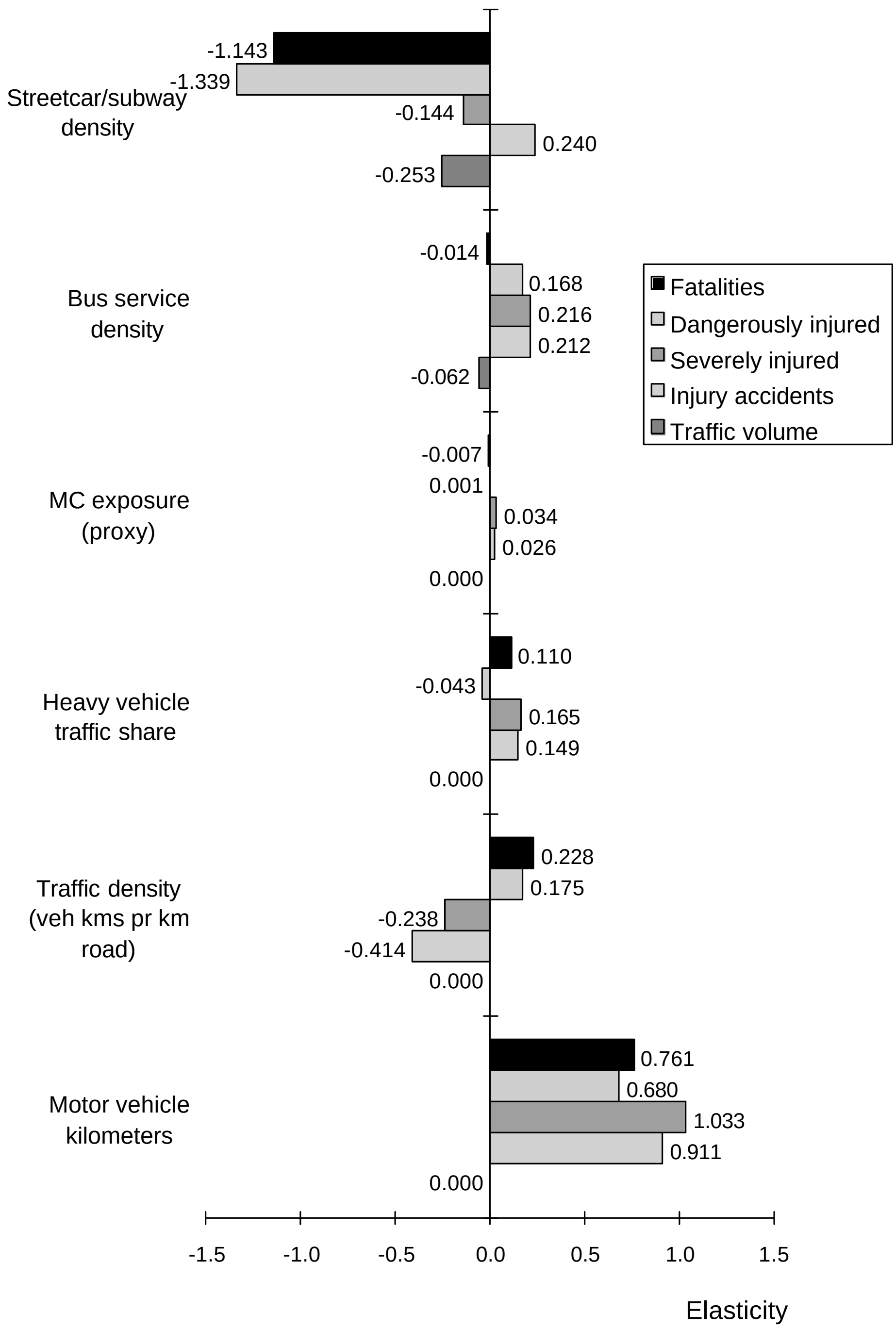

Figure 2: Exposure elasticities as of 1994. Accidents and victims by severity.

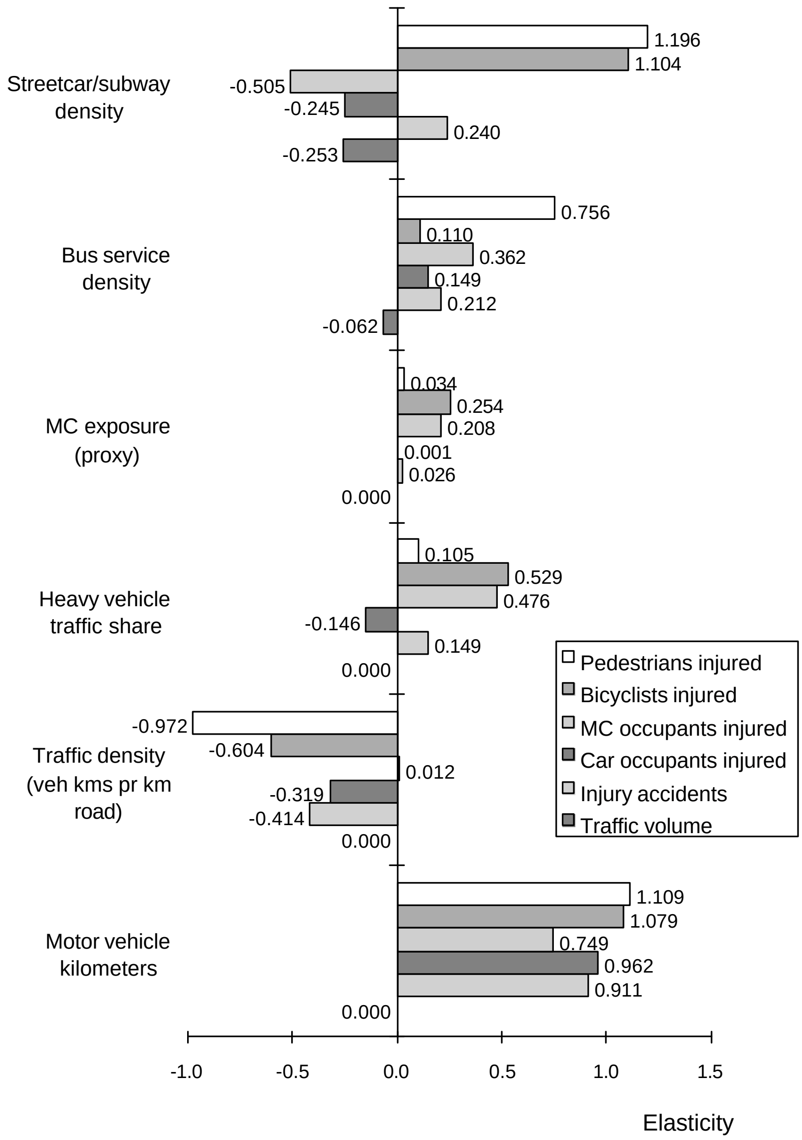

Figure 3: Exposure elasticities as of 1994. Injury accidents and victims by road user category.

Heavy vehicles[1] are more dangerous than private cars. The larger the *heavy vehicle share* of the traffic volume, the higher the injury accident frequency. However, fatalities and dangerous (i e, very severe) injuries increase less than the accident frequency, meaning that the average severity (persons severely injured per injury accident) does not increase. This may reflect the fact the truck driver himself is well protected and usually escapes the accident without (severe) injuries. Heavy vehicles appear to be particularly dangerous to two-wheelers, while car occupant

[1] I e, vehicles with more than 1 ton’s carrying capacity or more than 20 passenger seats.

injuries become less frequent when a large share of the traffic does *not* consist of private cars (figure 3).

Motorcycle exposure has a clear effect on motorcycle accidents but, on account of its small share of the exposure, a quite modest effect on the overall accident frequency[2].

Enhanced public transportation services tend to reduce the use of private cars and hence the total number of vehicle kilometers. A one per cent increase in the *density of bus service* lowers the overall traffic volume by an estimated 0.062 per cent. However, this is not sufficient to offset the exposure effect of the bus service: injury accidents increase by 0.212 per cent , i e by 0.264 (= 0.212 + 0.062) per cent as reckoned per vehicle kilometer (figure 2). This effect is dueprimarily to more *pedestrians* being injured, presumably on their way to or from the bus stop, but even car occupants and two-wheelers are exposed to a somewhat higher risk owing to the bus service (figure 3).

Similar and even stronger effects are found for public transportation by rail (streetcar or subway). Obviously, this kind of service does not entail increased risk or exposure for motorized road users, only for bicyclists and pedestrians.

Road infrastructure

The calculated effects of improved or extended road networks are exhibited in figures 4 and 5. The effects shown in these and the following graphs are all interpretable as long-term (equilibrium) effects, i e they incorporate effects due to changes in (optimal) car ownership. Also, it is assumed throughout that the heavy vehicles represent a constant share of the total traffic volume.

For analytical purposes, we decompose the supply of road infrastructure into two parts: (i) the *length* of the public road network (in kilometers per county), and (ii) the *accumulated real investment expenditure per kilometer* (national or county) road. We interpret the first component as a measure of *size*, while the second one may be understood as an economic measure of road *quality*[3].

An added supply of roads appears to generally increase the accident toll. This is true for (size) enlargements as well as for (quality) improvements.

The great bulk of this effect can be traced back to the fact that road use demand responds to shifts in supply. An extended or improved road network reduces the cost of travel by car and hence increases the demand for cars and road use.

The risk level (accidents or casualties per vehicle kilometer) is not very strongly affected, although there is a tendency for casualties to increase slightly more than proportionately with the traffic volume, when new roads are added to the network. The main reason for this is that a decrease in density (increase in road space) tends to augment the risk.

[2] The “elasticity” computed for motorcycle exposure should not be interpreted literally, since the independent variable used is only a proxy, which appears to capture bicyclist exposure as well.

[3] This measure is, of course, far from perfect, since property values and topographical conditions differ sharply between the counties, affecting the costs of road construction.

It should be noted, though, that the estimated partial effects of road infrastructure are generally not (very) significant (except the effect on car ownership). The uncertainty surrounding these elasticities is therefore considerable. Our confidence in these results is, however, strengthened by the relatively consistent and unambiguous pattern emerging. With one exception, all the elasticities shown in figures 4 and 5 are positive. The fact that bicyclist injuries tend to decrease with the length of the road network may simply be a cross-sectional exposure effect: The supply of road kilometers per inhabitant is larger in more sparsely populated counties, where distances are generally large and slow modes of travel comparatively unattractive.

Another word of caution is in order as well. One cannot draw the conclusion that every road investment, be it for extension or improvement, increases the accident toll. Certain types of road improvements or alterations are undoubtedly effective accident countermeasures (see Elvik et al 1997:149-242). What the TRULS model results do suggest, however, is that, given the way that road investment expenditures have been allocated over our period of observation (1973-94) in Norway, they have not – by and large – contributed to a smaller accident toll, nor to a significantly reduced risk as reckoned per unit of traffic. Their main effect has been to facilitate an increase in mobility.

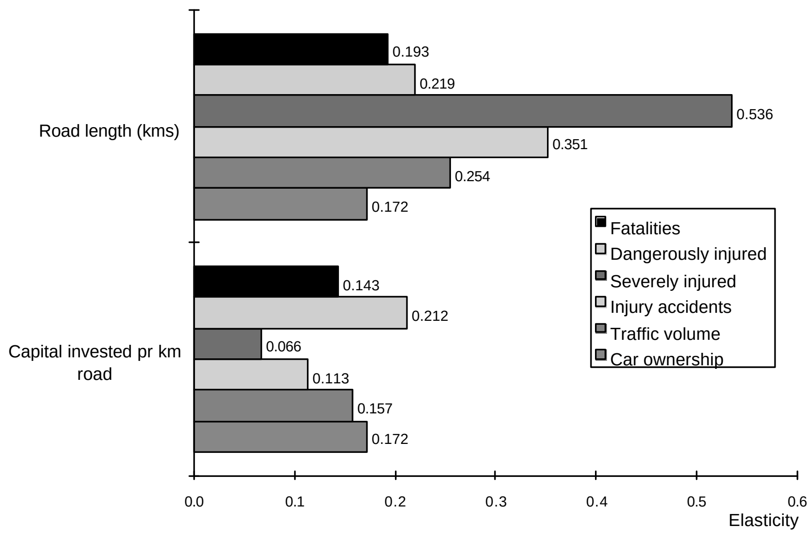

Figure 4: Road infrastructure elasticities as of 1994. Accidents and victims by severity.

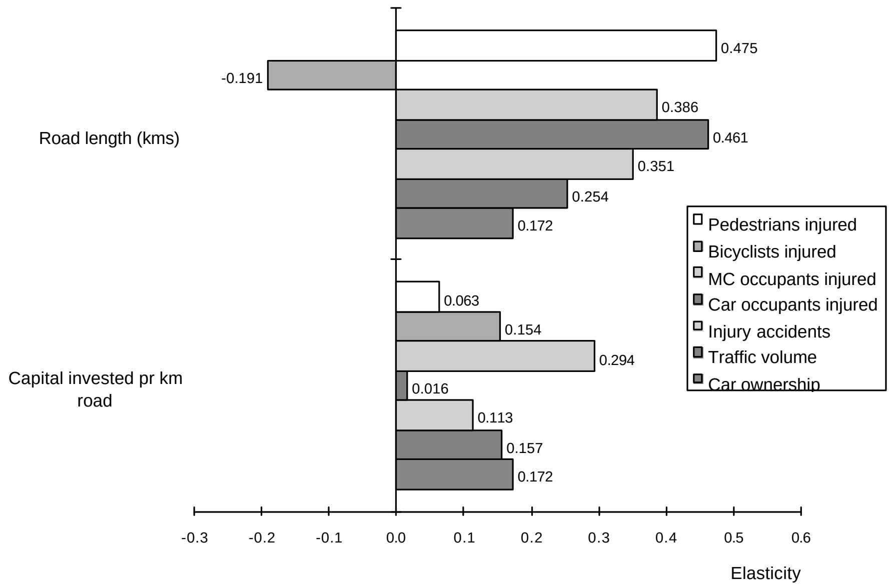

Figure 5: Road infrastructure elasticities as of 1994. Injury accidents and victims by road user category.

This finding is not very surprising in the light of recent knowledge on the road investment decision process. The respective benefits accruing from competing investment projects have little influence on the allocation of funds (Odeck 1991 and 1996, Elvik 1993 and 1995, Nyborg and Spangen 1996). The weight attached to safety benefits is particularly small (Fridstrøm and Elvik 1997).

Road maintenance

In figures 6 and 7 we show estimated elasticities with respect to road maintenance expenditure.

Again, it should be noted that coefficient estimates underlying these elasticities are generally not (very) significant, and that the effects are uncertain. Unlike the road infrastructure effects, the maintenance effects appear rather disparate and inconsistent. *By assumption*, the impact on car ownership and road use is zero.

Winter maintenance expenditure has an entirely insignificant effect on accidents and casualties, except for two-wheelers, where the effect is positive (i e, casualty increasing). This is most probably an exposure effect: improved winter maintenance makes motorcycling and bicycling possible even during winter.

Road marking expenditure appears to have a generally favorable effect on risk, although the effects are – again – quite uncertain and hardly significant, except for two-wheelers.

Our last category – "*miscellaneous maintenance expenditure*" - lumps together all other maintenance costs. The safety effect of these – although uncertain – appears generally unfavorable, as if car drivers tend to take advantage of improved maintenance so as to increase their speed. The generally positive sign of the severity effects may be an indication that such behavioral adaptation does in fact occur.

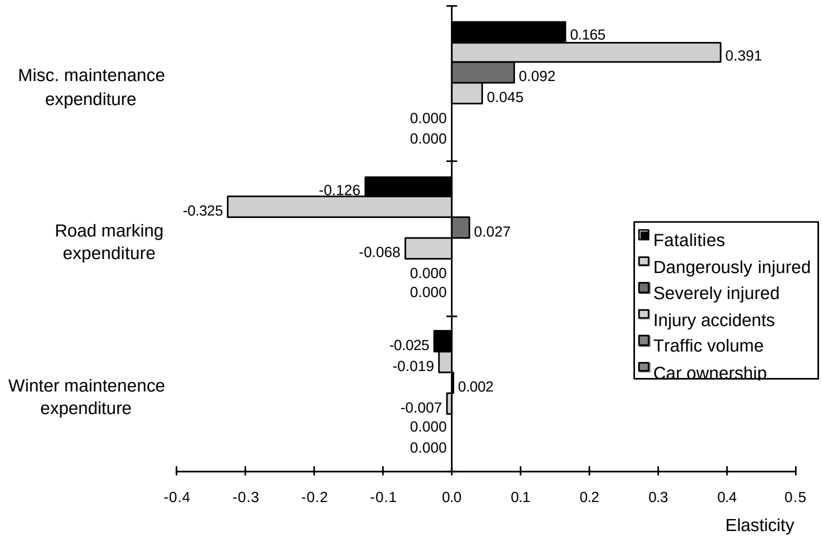

Figure 6: Road maintenance elasticities as of 1994. Accidents and victims by severity.

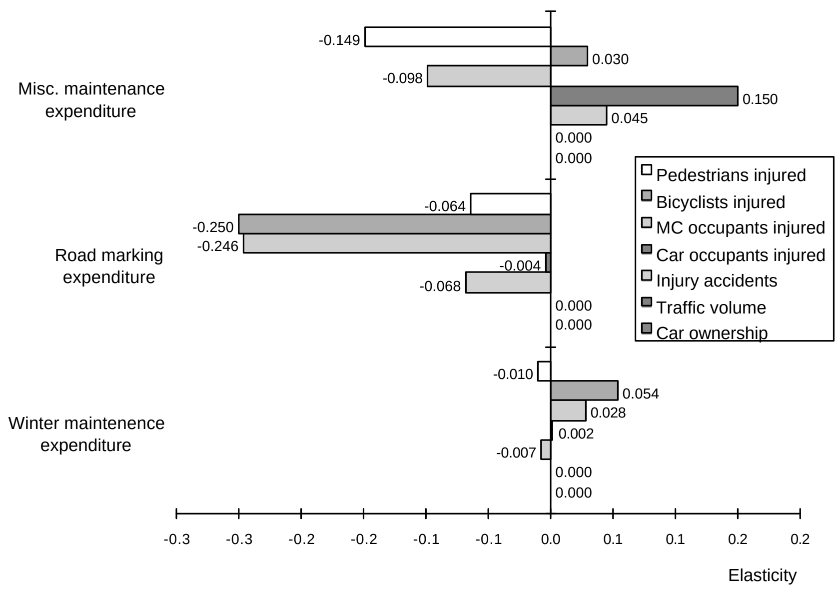

Figure 7: Road maintenance elasticities as of 1994. Injury accidents and victims by road user category.

Population

Car ownership and road use increase near-proportionately with the size (or density) of the population, other things[4] being equal. Accident and casualties increase less than road use, owing to the traffic density effect (figure 8).

Unemployment has a small, but highly significant, negative effect on road use, and an additional, barely significant effect on casualties.

The rate of (first quarter) pregnancy has a clearly significant, unfavorable effect on the injury accident frequency, but not on the number of very serious or fatal injuries.

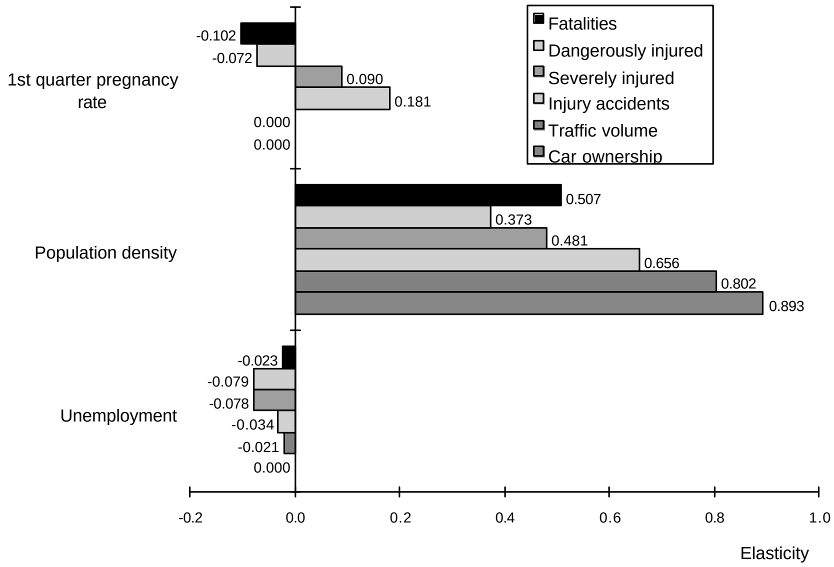

Figure 8: Population elasticities as of 1994. Accidents and victims by severity.

Income

Figures 9 and 10 show income elasticities for car ownership, road use, accident frequency and victims. The graphs are drawn under the assumption of a constant road network, so that traffic density increases at a rate identical to the vehicle kilometer growth.

The (private) income elasticity of aggregate, long-term (equilibrium) car ownership is estimated at more than one (1.18). For aggregate road use (and hence also for fatalities and very serious injuries), the long-term income elasticity is estimated at no less than 1.61 as of 1994. The short-term income elasticity of road use (assuming constant car ownership) can be inferred as the difference between the former two, i e at appr 0.43 (= 1.61 – 1.18).

[4] To be specific, the road network, public transportation supply, price levels and *per capita* income are assumed constant.

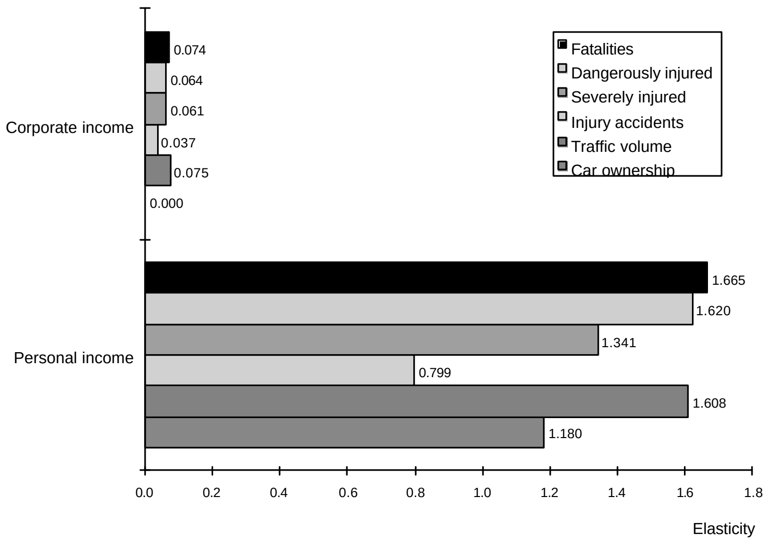

Figure 9: Income elasticities as of 1994. Accidents and victims by severity.

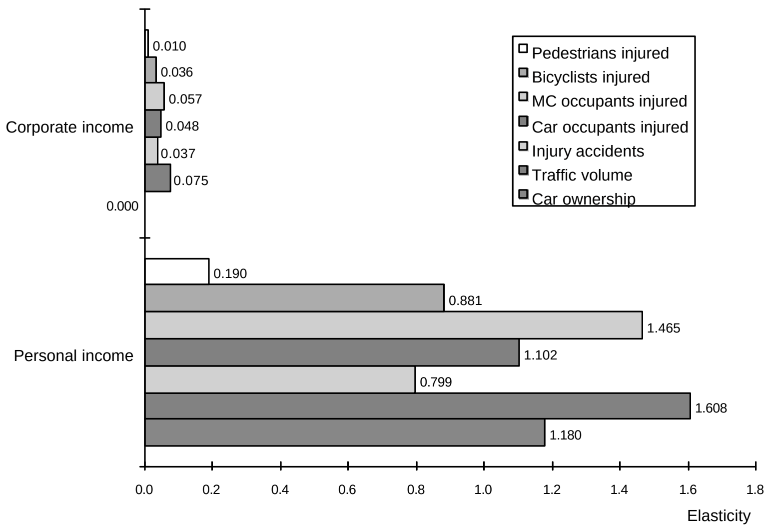

Figure 10: Income elasticities as of 1994. Injury accidents and victims by road user category.

A rising income level has a much smaller effect on pedestrian and bicyclist injuries than on car and motorcycle accidents (figure 10).

Corporate income has an almost negligible effect on road use as well as on accidents.

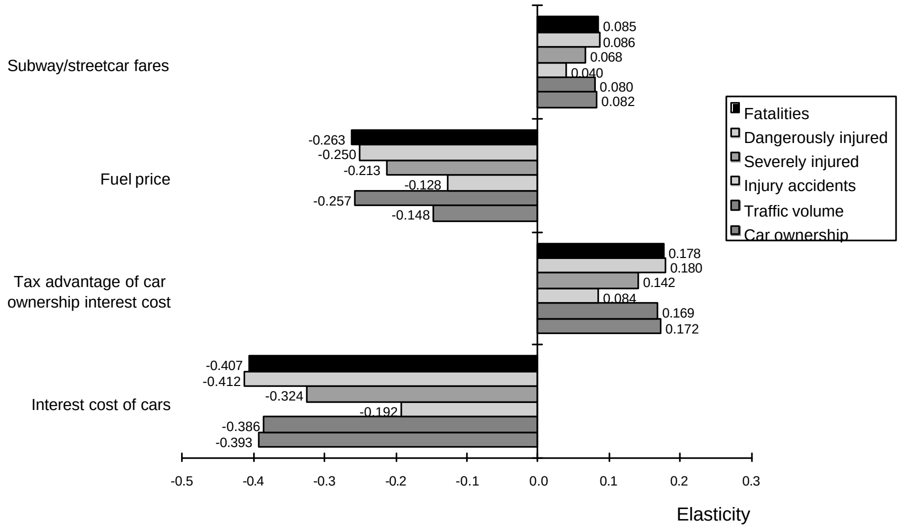

Figure 11: Price elasticities as of 1994. Accidents and victims by severity.

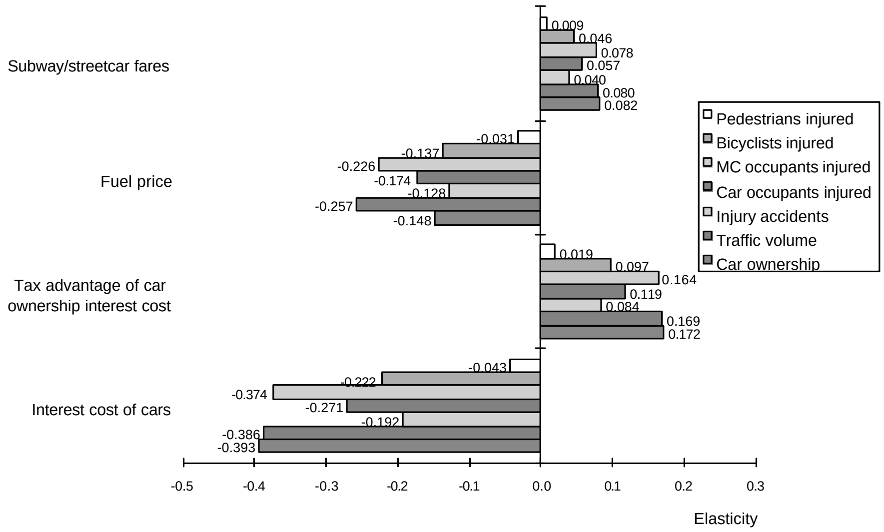

Figure 12: Price elasticities as of 1994. Injury accidents and victims by road user category.

Prices and tax rates

Price elasticities are shown in figures 11 and 12.

A most important price variable (under Norwegian conditions) is the current *rate of interest*, which strongly affects the equilibrium car ownership and hence road use, accidents and fatalities. For car ownership and road use, as well as for fatalities and very severe injuries, its elasticity is estimated at close to –0.4.

The *tax advantage due to interest payment deductibility* works in the opposite direction, dampening the effect of increased interest rates.

The *fuel price elasticity* as of 1994 is estimated at –0.257 for overall road use (vehicle kilometers). More than half of this effect (–0.148) is due to reduced (equilibrium) car ownership. Some households no longer find it worthwhile to keep a(n extra) car when its use becomes too expensive.

In the short run, when car ownership is constant, the price elasticity is only –0.109 (= –0.257 + 0.148). Recall, however, that the fuel price elasticity increases strongly with the initial price level.

Obviously, the fuel price effects on road use translates into similar effects on traffic casualties.

Public transportation fares have a modest, but clearly significant cross-price effect on motor vehicle road use and hence also on accidents and fatalities, although not for pedestrians. Fatalities may be expected to increase by 0.085 per cent for each per cent increase in the streetcar/subway fares.

Weather

Weather conditions have a marked impact on accident risk, although the direction of effects may in some cases seem surprising (figures 13 and 14).

In Norway, accidents become less frequent when the ground is *covered by snow*. We believe this is due to the fact that a certain layer of snow serves to reflect light and hence strongly enhances visibility at night.

The risk reduction is also larger the deeper the snow is. This is probably a *snowdrift* effect. The formation of snowdrifts along the roadside serves to reduce the frequency of single vehicle injury accidents, as they prevent cars from leaving the road and/or dampen the shock whenever a car is straying aside (Brorsson et al 1988). On the other hand, snowdrifts tend to limit the road space and may thus increase the risk of head-on collisions, as when cars are thrown back into the road after hitting the snowdrift.

During *days with snowfall*, however, the accident frequency goes up. At the same time, severity is reduced sufficiently to more than offset the increase in accident frequency, at least as far as fatalities are concerned. This is most probably a risk compensation effect: motorists reduce their speed on slippery surface, perhaps not quite enough to keep the injury accident frequency constant, but certainly enough to strongly reduce the consequence once an accident does occur.

Does it matter how much snow is falling? One might imagine that heavy snowfall creates a particularly risky traffic situation. The variable “*heavy snowfall*” is defined as the percentage of snowfall days during which the precipitation exceeds 5 millimeters (in water form). This effect, too, is generally positive for all road user groups, although too small to be statistically significant.

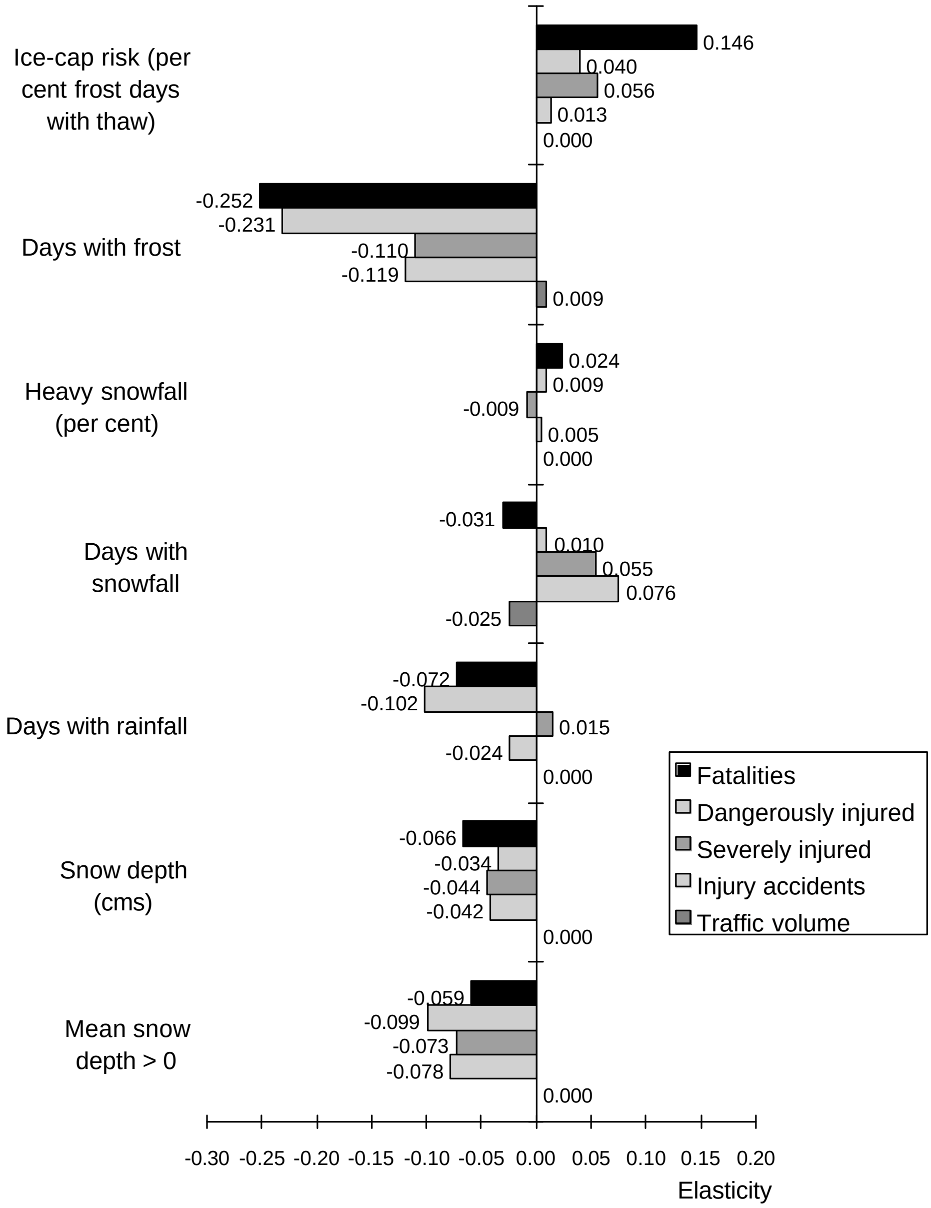

Figure 13: Weather effects as of 1994. Accidents and victims by severity.

An even clearer example of behavioral adaptation is seen in the *frost* variable. The monthly number of days with temperatures dropping below has a negative (i e, favorable) effect on the accident toll, especially on the most severe injuries.

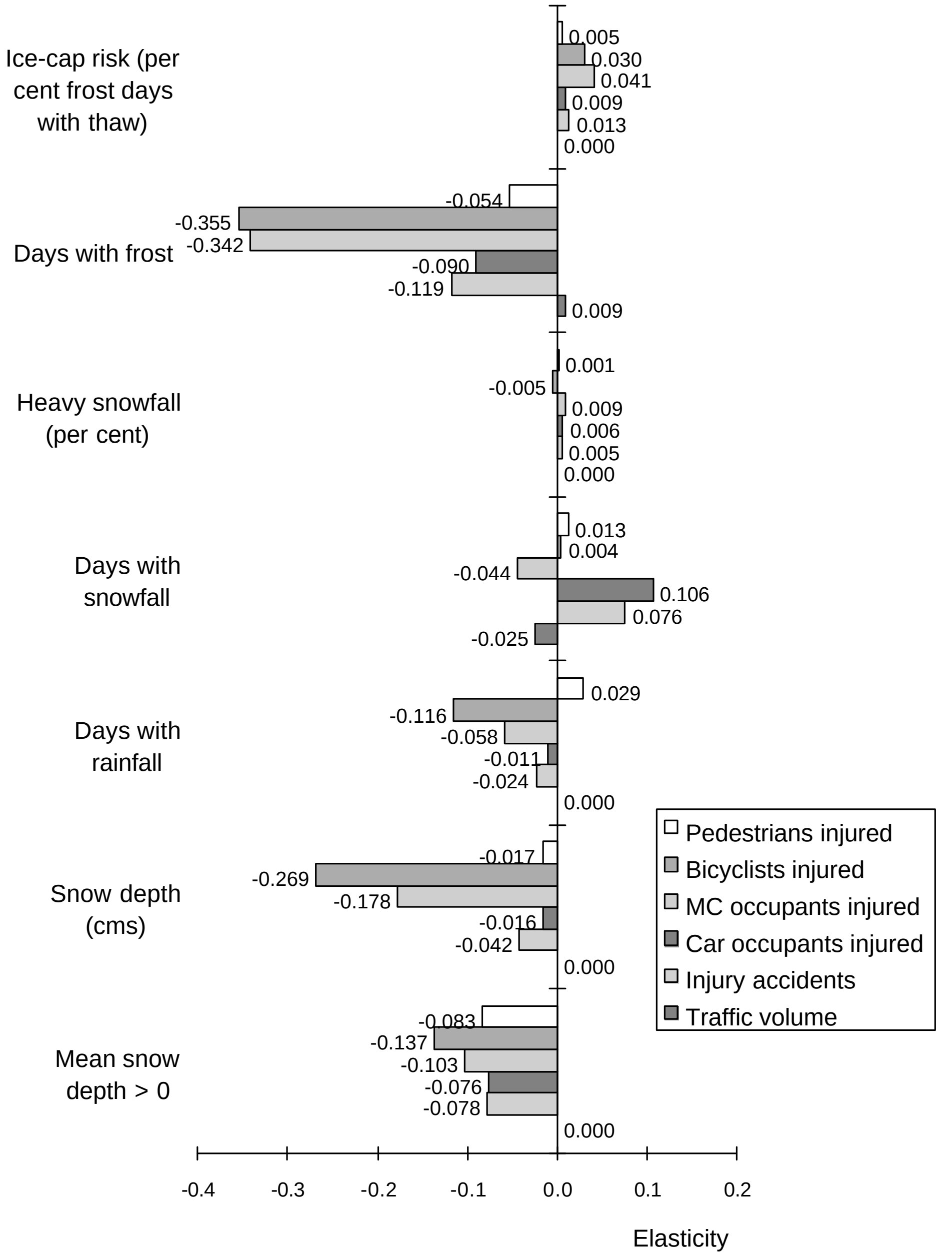

Figure 14: Weather effects as of 1994. Injury accidents and victims by road user category.

Comparing the two-wheeler injury models to the pedestrian and car occupant injury models, one notes, however, a much stronger, negative effect for bicyclist and motorcyclists. This suggests that part of the frost effect found in the main model may be due to a reduction in two-wheeler exposure, not entirely controlled for through our MC exposure proxy. Yet, it is interesting to note that even for car occupants, the estimated effect is negative.

When the temperature drops below freezing at night, but rises above 0 °C during the day, certain particularly hazardous road surface conditions may arise. If snow melts during the day, wetting the road surface and forming a cap of ice at night, road users risk being surprised by some extremely slippery patches on a road surface that generally appears clear and dry, suitable for considerable speed. The "*ice cap risk*" variable measures the percentage of frost days during which the maximum temperature is above freezing. Its elasticity generally has the expected positive sign.

Rainfall has a seemingly negative (i e, favorable) effect on the accident count. Again, however, it appears that the effect is due mainly to reduced exposure among the unprotected road users, especially bicyclists. For car occupants, the effect is virtually zero.

Daylight

In figures 15 and 16 we show how the (lack of) daylight ("darkness") during various parts of the day affects *risk*.

These graphs differ from the previous ones in that *only direct effects* on casualties are incorporated in the elasticities. That is, the (seasonally and regionally conditioned) association between daylight and traffic volume is not taken account of; the graphs show casualty elasticities *given* motor vehicle road use.

Lack of daylight during the ordinary working hours (9 a m to 3 p m)[5] does not have noticeable effects on the accident frequency or severity.

Darkness during the traffic peak hour periods (7 to 9 a m and 3 to 5 p m) does, however, have a clearly significant impact on risk, especially for pedestrians. For bicyclists, the estimated association is negative ("favorable"), presumably an exposure effect.

An even stronger effect is due to dark evenings (5 to 11 p m). Again, the largest risk increase applies to pedestrians, while two-wheelers are probably subject to reduced exposure and hence also to a lower accident toll. Car occupant injuries are significantly more frequent when the evenings are dark.

The length of the twilight period does not, in general, have any significant impact on casualty rates, except for bicyclists and pedestrians. Here the effect is negative (favorable), when the amount of daylight is controlled for.

[5] This variable has non-zero values during the winter months in the northernmost counties, reaching 360 (minutes per day) in Finnmark in December.

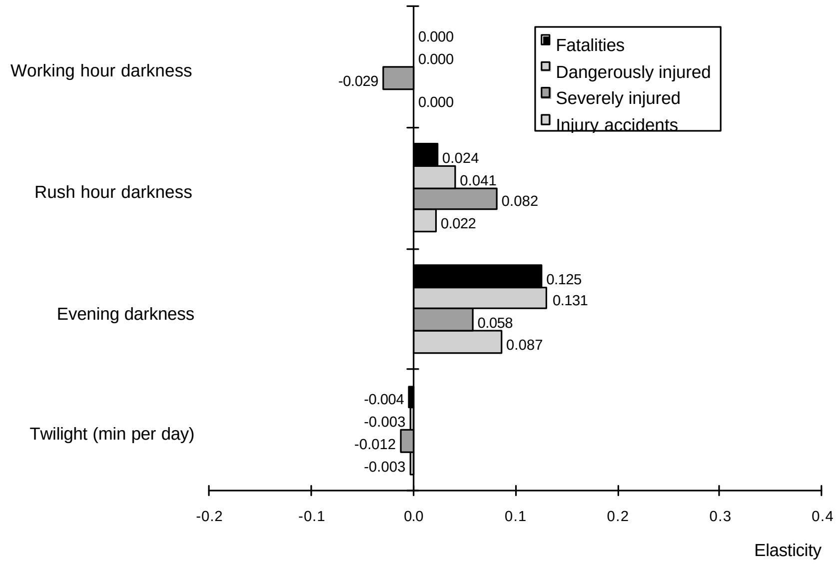

Figure 15: Direct daylight effects, conditional on motor vehicle road use. Accidents and victims by severity.

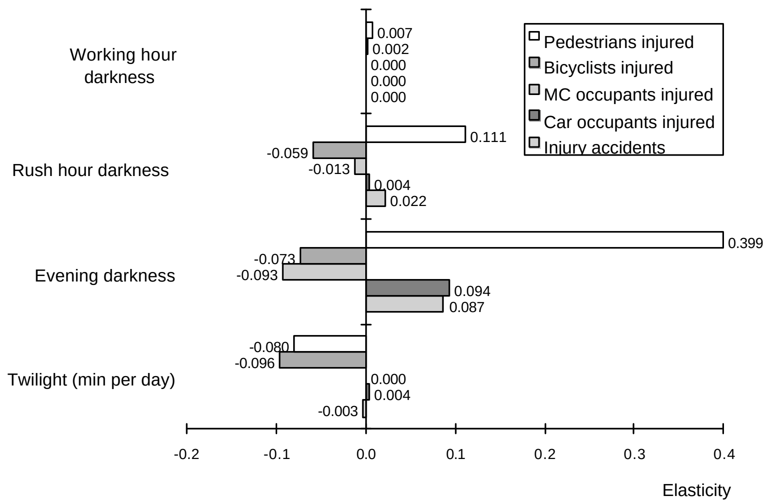

Figure 16: Direct daylight effects, conditional on motor vehicle road use. Injury accidents and victims by road user category.

Seat belts

Seat belts are an effective injury countermeasure (figure 17). A 10 per cent increase in the number of car drivers *not* wearing the belt (from – say – the 12 per cent rate estimated in 1994, to 13.2 per cent) will increase the number of car occupant injuries by some 3 per cent and the number of fatalities by some 0.6 per cent. It appears that seat belts are more effective in preventing less severe injuries than in saving lives.

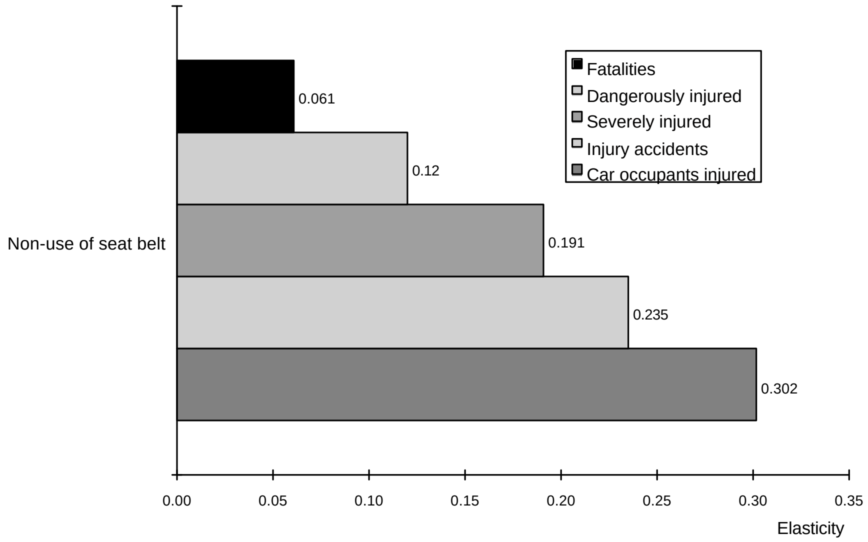

Figure 17: Seat belt effects as of 1994.

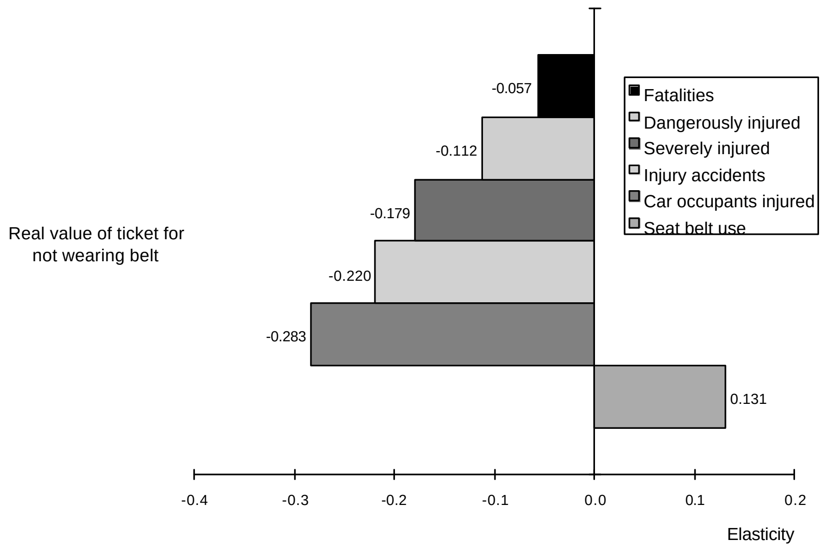

Figure 18: Seat belt ticket elasticities as of 1994.

In the TRULS model, we find no sign that seat belts give rise to behavioral adaptation on the part of car drivers, in such a way as to represent an increased hazard to pedestrians, as was once suggested by Peltzman (1975).

By combining the elasticities found in the seat belt model with the elasticities shown in figure 17, we are able to calculate the estimated effect of increasing the (real value of the) ticket fine for not wearing a safety belt. This ticket runs at NOK 500 as of 1994.

A 10 per cent increase in this fine corresponds, as of 1994, to a 1.3 per cent increase in the rate of seat belt use, i e from 88 to 89.2 per cent. This corresponds to an almost 10 per cent decrease in the rate of *non-use* (from 12 to 10.8 per cent), which translates into a 2.8 per cent decrease in the number of car occupant injuries and a 2.2 per cent reduction in the total number of injury accidents.

The gradual reduction of the real value of the ticket due to inflation will, by assumption, have opposite effects.

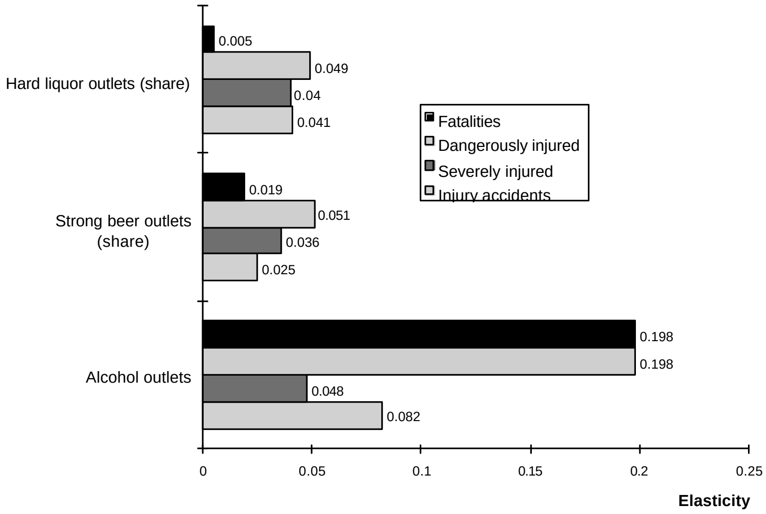

Figure 19: Alcohol availability effects as of 1994. Outlets. Accidents and victims by severity.

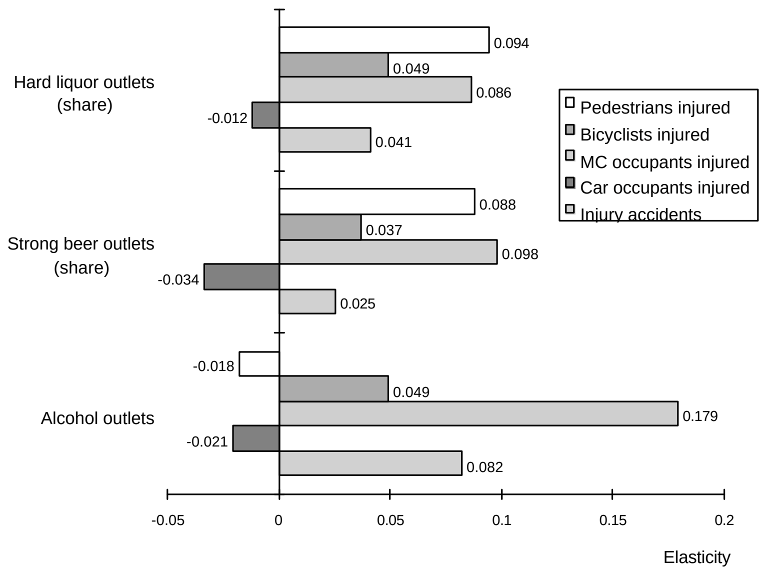

Figure 20: Alcohol availability effects as of 1994. Outlets. Injury accidents and victims by road user category.

Alcohol availability

Access to alcohol is more severely regulated in Norway than in most other western industrialized countries. Wine and liquor are sold only from state monopoly stores, generally found only in larger townships, and even beer sales are subject to licensing by the municipal assembly. Restaurants also need a central or local government license in order to serve alcoholic beverage.

More than half the counties have less than one alcohol outlet (shop) per 3 000 square kilometers. Even beer sales have been heavily restricted in some counties, although more so in the 1970s and early -80s than at present. A few municipalities still maintain an absolute ban on any kind of alcoholic beverage being served or sold. In the TRULS model we decompose the availability of various forms of alcohol into six parts. *By assumption*, alcohol availability does not affect car ownership or road use.

One variable ("*alcohol outlets*") measures the total number of *shops* per 1000 inhabitants. A second one ("*strong beer outlets - share*") measures the percentage of shops allowed to sell beverage stronger than lager beer (4.5 per cent alcohol by volume). A third variable ("*hard liquor outlets - share*") measures the percentage of these, in turn, that are wine/liquor stores.

A similar decomposition is applied to *restaurants*. General availability is measured in terms of "*restaurants licensed to serve alcohol*" per 1000 population. Secondly, we measure the share of these that are allowed to serve wine or liquor – i e, not only beer ("*wine/liquor licenses – share*"). Thirdly, we measure the share of these, in turn, which may serve liquor ("*hard liquor licenses – share*").

In figure 19, the alcohol outlet effects come out strikingly consistent, yielding positive casualty elasticities for every degree of severity, with respect to every type of alcohol. Judged by these estimates, the restrictive Norwegian alcohol policy has helped prevent a certain number of road accidents and fatalities.

When the effects are partitioned between different road user groups, the picture becomes more mixed (figure 20). Apparently, an increase in the availability of alcohol has an impact on pedestrian, bicyclist and motorcyclist injuries, but not on car occupant injuries.

Another set of surprising results relates to the density of restaurants with a license to serve alcohol. In general, the effects of restaurant density are negative (figures 21 and 22). This is true in particular of wine restaurants (as opposed to beer gardens etc), suggesting that only the latter category – if any – represents a problem in relation to road safety.

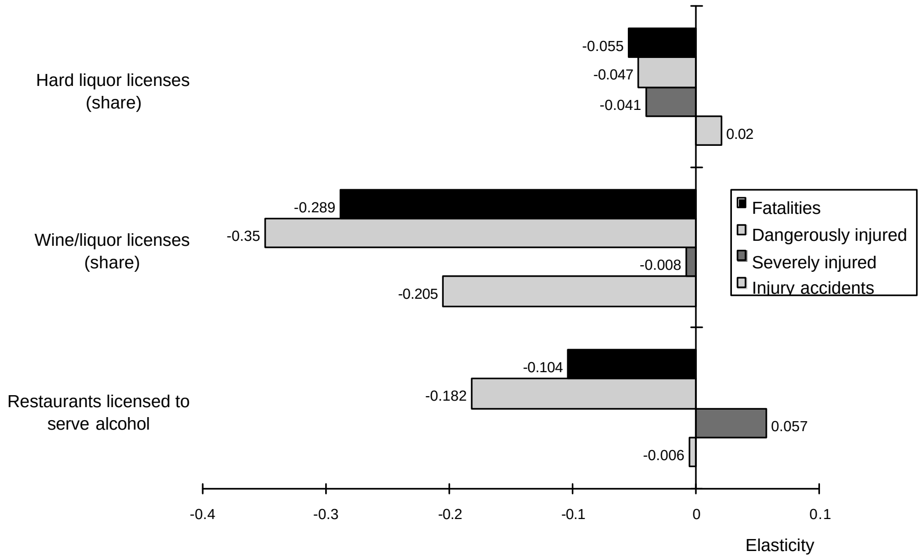

Figure 21: Alcohol availability effects as of 1994. Restaurants. Accidents and victims by severity.

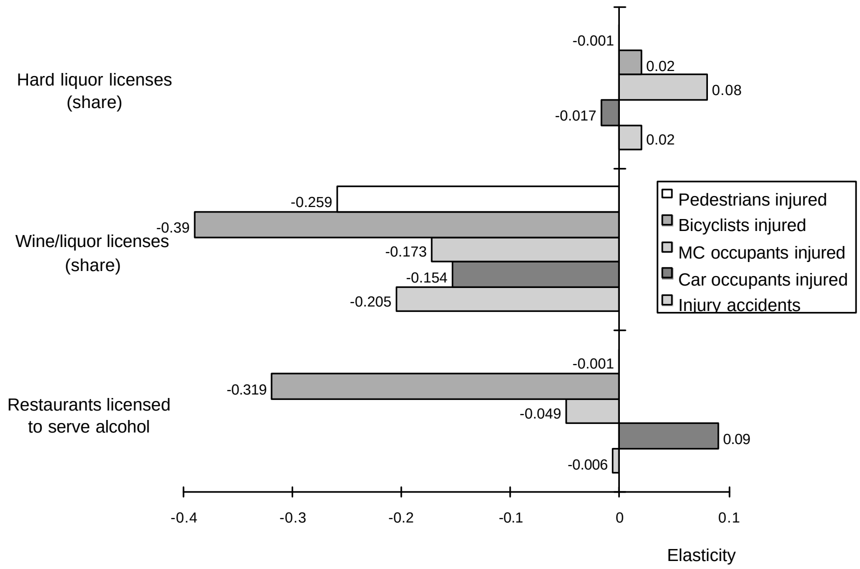

Figure 22: Alcohol availability effects as of 1994. Restaurants. Injury accidents and victims by road user category.

Calendar effects

The calendar *per se* has a certain impact on human activity and hence also on road casualties. This is shown in figures 23 and 24[6].

The *Easter holiday* has a pronounced traffic generating effect, by around 5 per cent (on a monthly basis) at the onset as well as at Easter end. Injury accidents increase at about the same rate as the traffic at *Easter start*, and fatalities go up by almost 20 per cent.

Behind these overall accident statistics lie a 12 per cent *increase* in car occupant injuries and a clear *decrease* in two-wheeler and pedestrian injuries. Few people walk or bike to their Easter resort.

At *Easter end*, the congestion is apparently so heavy that fewer injury accidents and fatalities occur than should "normally" follow from the (increased) exposure.

The extra activity generated during the month of *December* translates into an about 25 per cent higher traffic volume and an almost equally large increase in fatalities.

Holidays and vacation ("*leisure days*") dampen the overall (domestic) mobility and hence also the number of road casualties. The number of days in a given month ("*length of month*") also has an obvious effect – not forgotten in the TRULS model – on total vehicle kilometers and their accident toll.

Time trend

The injury accident equation comes out with a highly significant time trend effect. As of 1994 the trend elasticity is calculable at –0.454 for injury accidents (fig 25). Note, however, that the trend variable is defined as years passed since 1945, so that a one per cent increase in this variable corresponds (as of 1994) to a time lapse of almost half a year. Thus the interpretation of this elasticity is that there is an autonomous safety improvement taking place over time, which – at present – tends to reduce the number of injury accidents by approximately 0.5 per cent every six months.

For fatalities, an almost equally strong trend effect is estimated, while for the number of severe injuries the effect appears to be more than six times stronger.

An interesting insight is gained when the trend effect is differentiated between road user groups (fig 26). Here, one notes that there is no independent trend effect for car occupant injuries (the small positive effect shown is statistically insignificant). The reduction in car occupant risk that has taken place during 1973-94 is, in other words, fully explained by the independent variables of the model. A most important single factor here is no doubt the escalated use of seat belts.

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[6] Note that in these diagrams, the effects shown for December, Easter start and Easter end are not elasticities in the traditional sense, but (approximate) relative changes associated with the respective dummy variables. For instance, injury accidents are about 5 per cent (= $e^{0.050} - 1$) more frequent during a month comprising the *start of Easter*, other independent variables being equal.

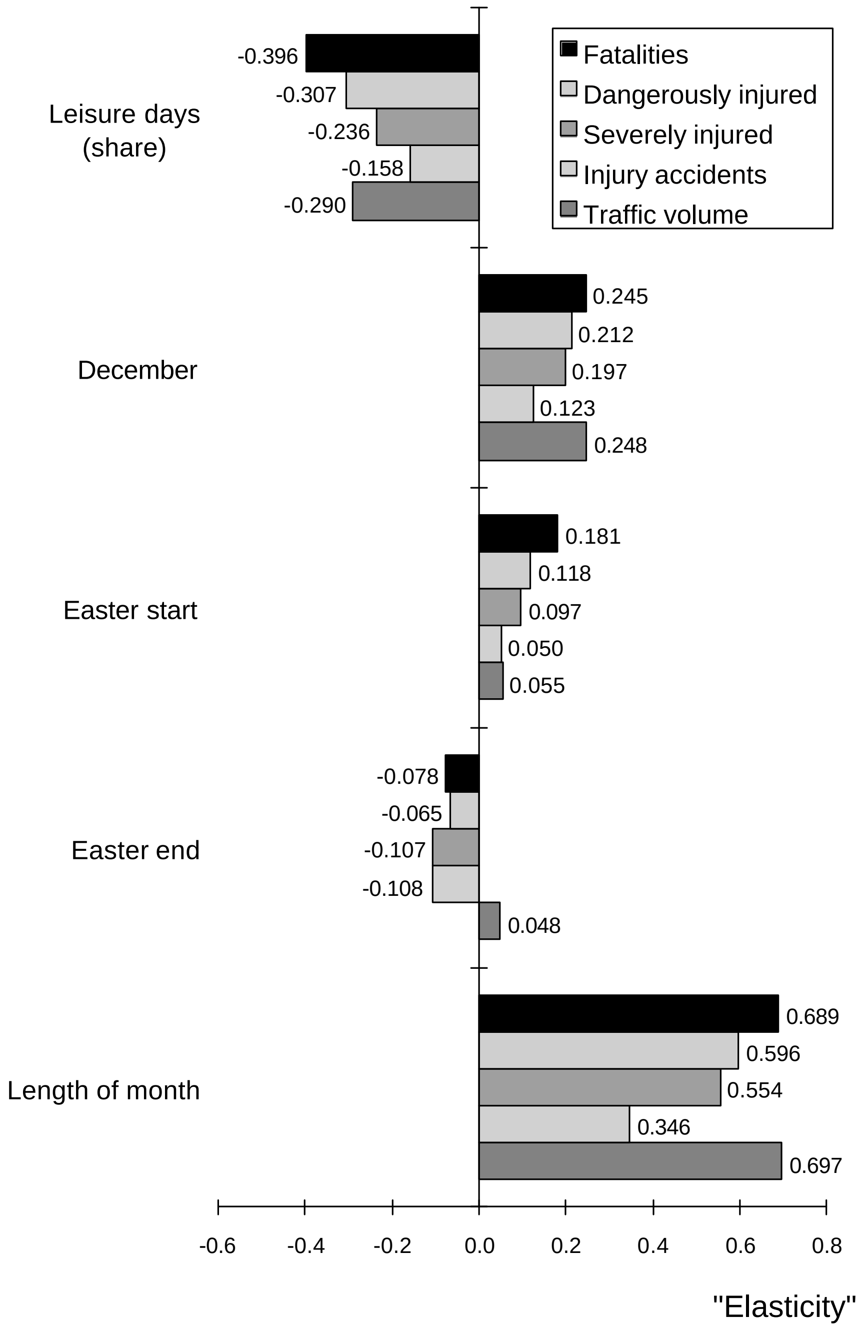

Figure 23: Calendar effects as of 1994. Accidents and victims by severity.

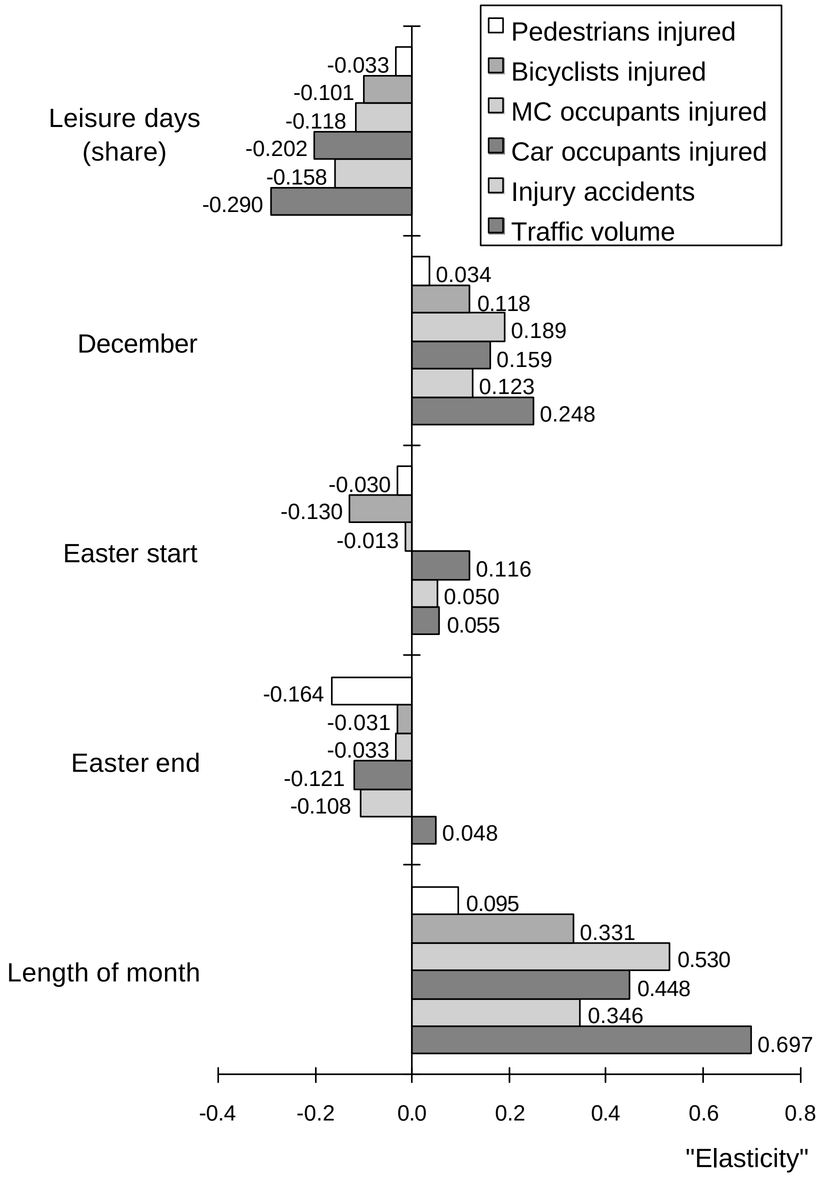

Figure 24: Calendar effects as of 1994. Injury accidents and victims by road user category.

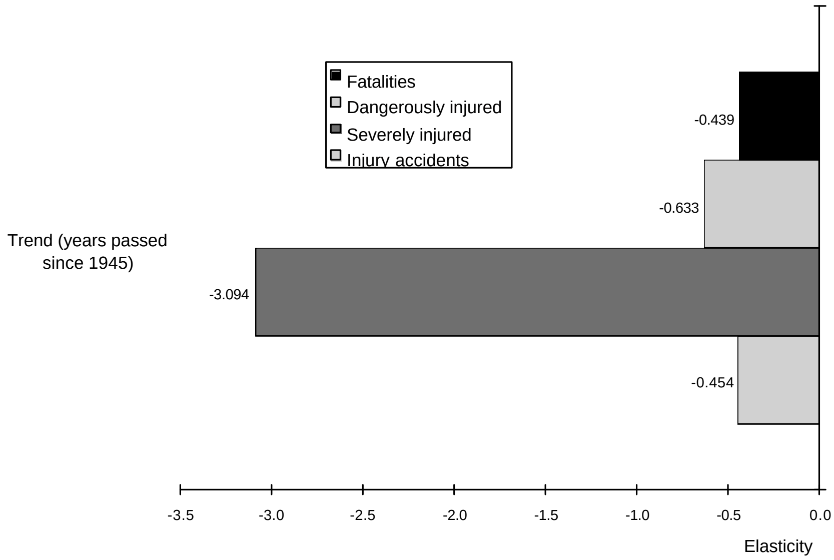

Figure 25: Trend effects as of 1994. Accidents and victims by severity.

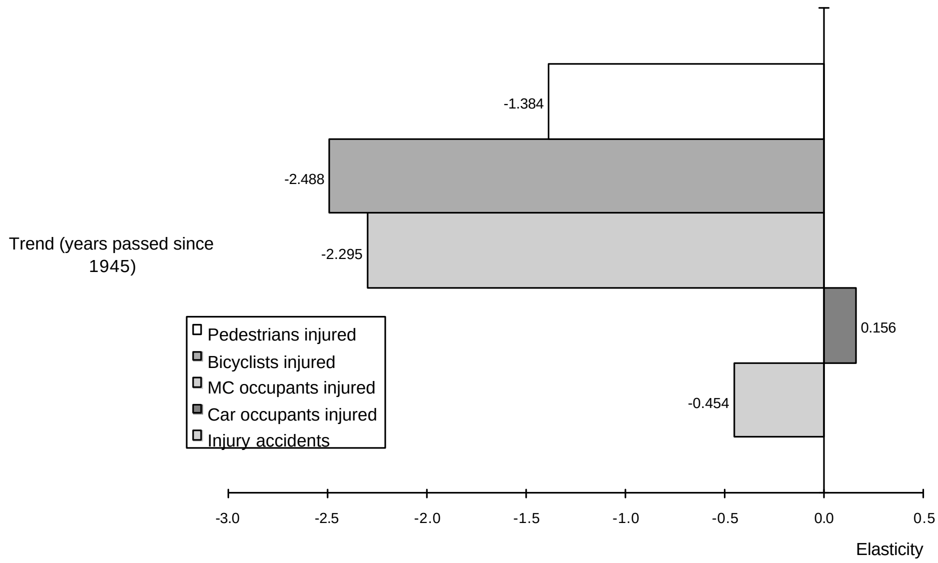

Figure 26: Trend effects as of 1994. Injury accidents and victims by road user category.

For two-wheelers and pedestrians, however, the trend effects are all the stronger. Bicyclist injuries decrease by no less than 5 per cent annually, other independent variables being equal, and pedestrian injuries by almost 3 per cent. It should be understood that large parts of these effects might be due to reduced (relative) exposure, not captured in the TRULS model. As the slower modes represent a steadily reduced part of total kilometers traveled, the frequency of accidents involving these modes – as reckoned per motor vehicle kilometer – naturally becomes lower.