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Chapter 3

SNUS-2.5, a Multimoment Analysis of Road Demand, Accidents and their Severity in Germany, 1968 – 1989

(*Straßenverkehrs-Nachfrage, Unfälle und ihre Schwere 2.5*)

Ulrich Blum

and

Marc Gaudry

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Contents

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List of Charts and Figures

List of Tables

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3 SNUS-2.5, A Multimoment Analysis of Road Demand, Accidents and their Severity in Germany, 1968 – 1989

(*Straßenverkehrs-Nachfrage, Unfälle und ihre Schwere 2.5*)

Ulrich Blum
Marc Gaudry

3.1. Context[1]

The present article presents an improved and refined version of the SNUS-1 model (GAUDRY and BLUM 1993) documented only in French. The greatest difficulty faced in the development of the model did not have to do with structure – the multilevel structure is straightforward – but with the specification of the employment activity variable, due to the specifics of the German economy,

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[1] **Acknowledgements.** This research was made possible by support from the DFG (*Deutsche Forschungs-Gemeinschaft*), the *Alexander von Humboldt-Stiftung* of Germany, the National Sciences and Engineering Research Council of Canada (NSERCC) and by Marc Gaudry's tenure as a 1998 *Centre National de la Recherche Scientifique* (CNRS) researcher at BETA, *Université Louis Pasteur* and UMR CNRS 7522. The authors are grateful to many others who helped with the data base, estimations and interpretations, including Andreas Althoff, Benoit Brillon, Francine Dufort, Stéphane Gelgoot, François Fournier, Pierre Langlois, Falk Kalus, Sylvie Mallet, Robert Simard and Liem Tran. Earlier versions of this chapter were presented in 1998 at the September BASt-conference on road safety held at Bergisch Gladbach and at the November 26-27 international conference "*La modélisation de l'insécurité routière par l'approche DRAG*/The DRAG approach to road safety modelling" held in Paris under the auspices of the *Institut National de Recherche sur les Transports et leur Sécurité* (INRETS), The Swedish Foundation for Research in Transportation (KFB) and the *Société de l'assurance automobile du Québec* (SAAQ) which has supported the development of the international DRAG network since 1995.

and with the proper formulation of the role of vehicle stocks in the road demand models. Moreover, we consider the following aspects to be special in the context of an analysis of Germany:

- there exist no general speed limits on motorways, i.e. about 70% allow unlimited speed today, and in the Sixties, when our analysis starts, this share was even higher;
- the country is large compared with other regions were the DRAG-methodology is employed, and it possesses high car ownership levels and an important car industry that sees the German infrastructure as an appropriate testing ground;
- Germany is poly-central, its infrastructure resembles a grid, whereas France's is almost a hub-and-spoke system, as compared for instance to Norway's line;
- unification is not yet included because of lagging data availability and, thus, problems to compensate for the structural break in data series.

In terms of econometric analysis, we were led to apply the TRIO-LEVEL algorithm (see Ch. 12) in new ways, both in the analysis of the functional forms and the evaluations of multi-moment determinations of the models.

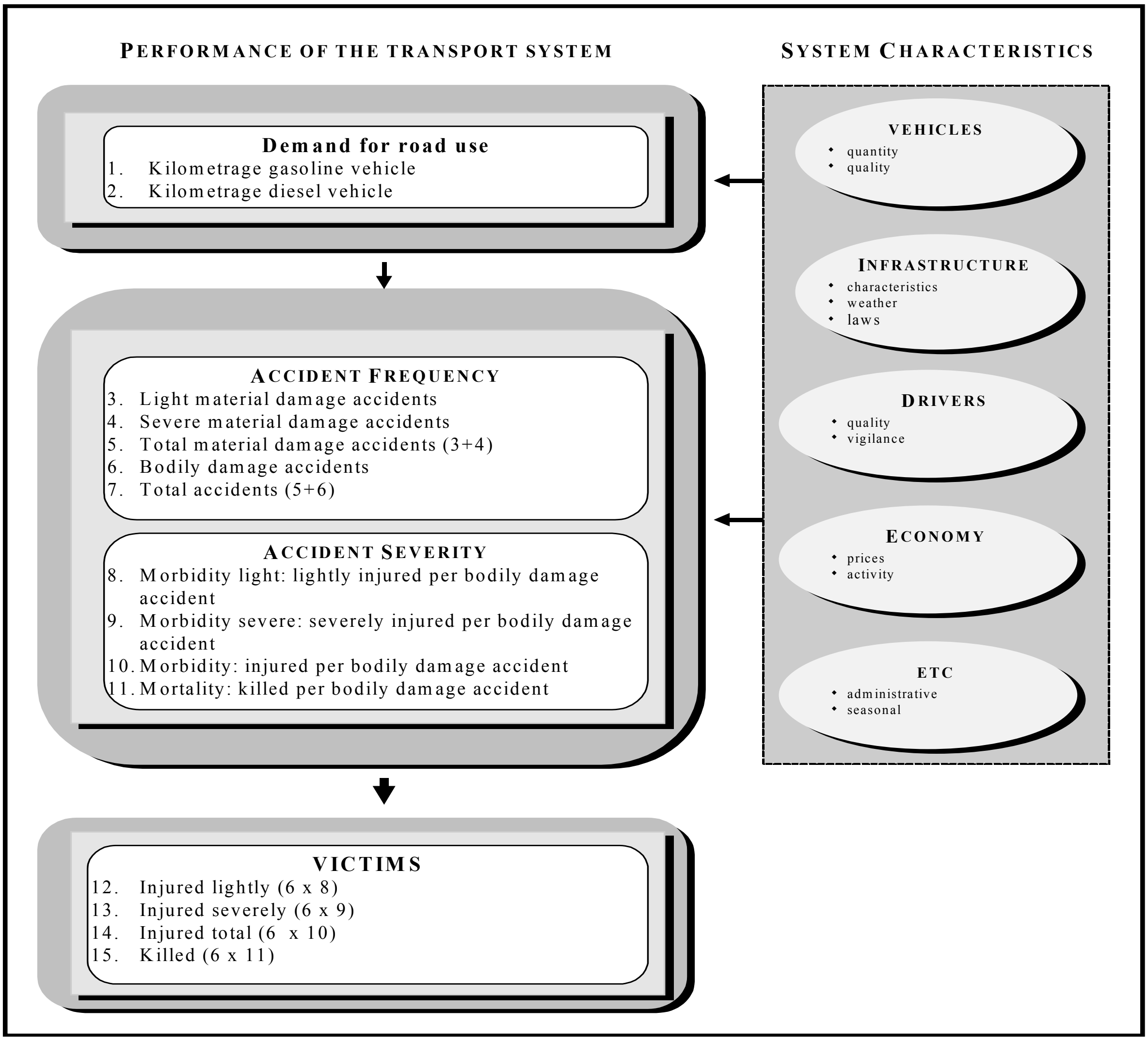
Our analysis is primarily in terms of the first moment (expected value) until Section 3.4.2 where it is extended to higher moments. Up to that point, we will report principally on elasticities, without stating the t-statistics associated with model parameters : these can be found in Appendix 3.1.

3.2. Structure of model

3.2.1 The dependent variables

As shown in Diagram 3.1, inspired by Jaeger (1998), no speed variable or congestion data are available in the German context. As they cannot be observed directly, some interpretation of results will require taking them into account. German data do not make it possible to distinguish between injury and fatal accidents despite the fact that the number of injured and killed victims are recorded.

Diagram 3.1. Dependent variables and their relations in SNUS-2.5

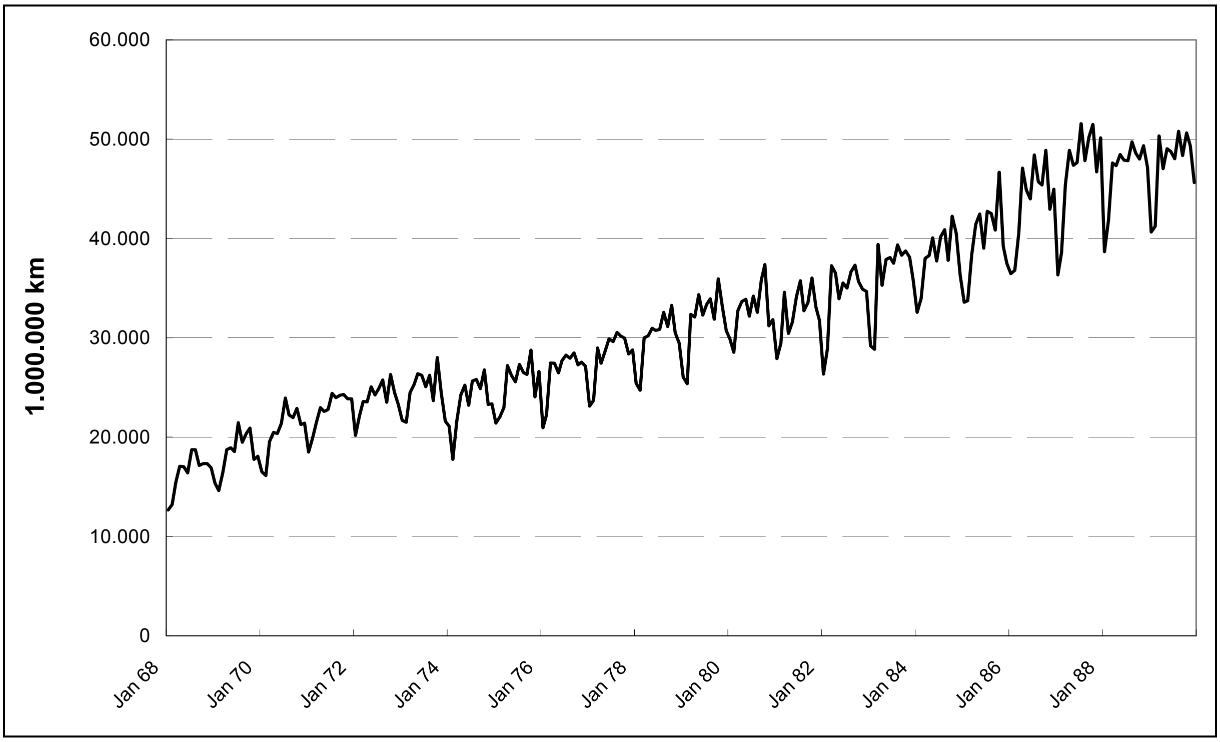


3.2.2 Visual analysis of the dependent variables

3.2.2.1 Road demand

As Appendix 1 makes clear, road demand was expressed by the kilometers driven with gasoline (KMBL) and diesel vehicles (KMDL). The original variables, monthly gasoline and diesel consumption, were transformed by dividing them by their specific consumption rates. These two variables taken together are used in the accident equations as measure of exposure (KML). In the severity equations, a gasoline car use index was computed that captures the kilometrage driven by gasoline cars relative to that of all cars (GCUI).

Graph 3.1. Road demand: kilometers driven by gasoline and by diesel vehicles



3.2.2.2 Accident Frequency

Accidents were available in two categories with their respective subcategories and aggregates:

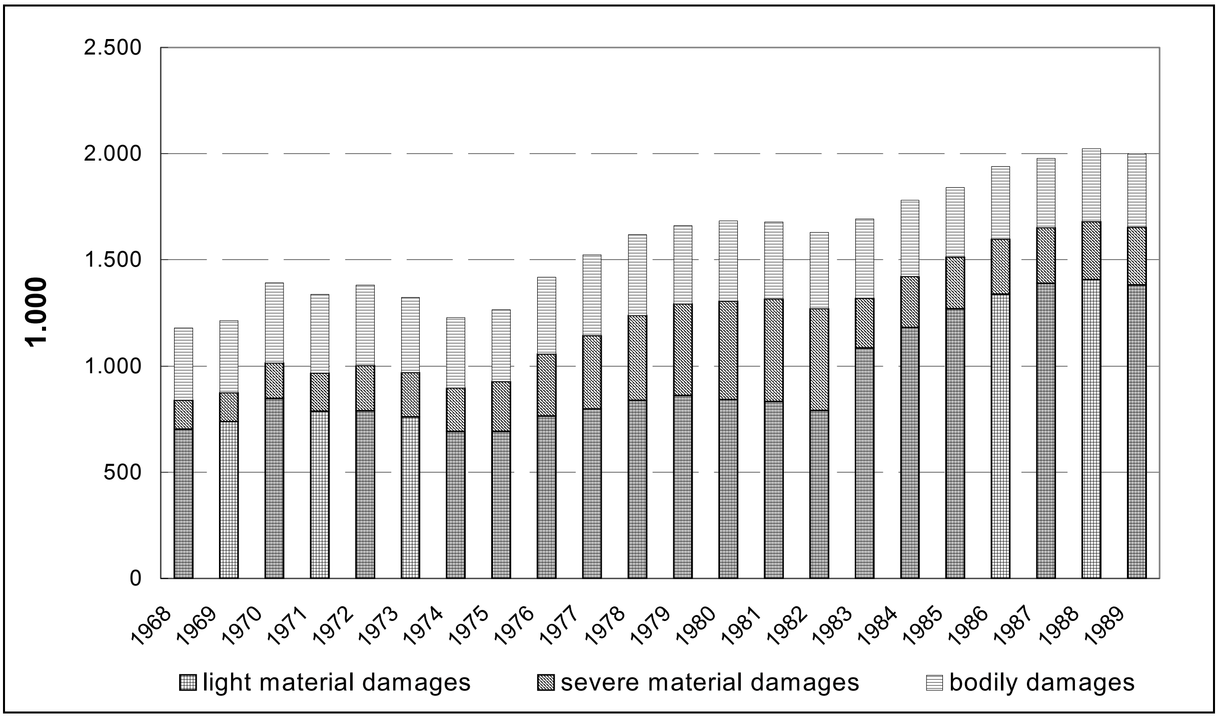
- accidents with light material damage (ULSS) and severe material damage (USSS) according to a delimitation of 1000 DM; from 1983 onwards 3.000 DM both add up to accidents with material damage (USS);
- accident with personal damage (UPS); if this type of accident is observed, a parallel material damage is not counted;
- total accidents as the sum of personal and material damage (UG=USS+UPS).

3.2.2.3 Accident severity

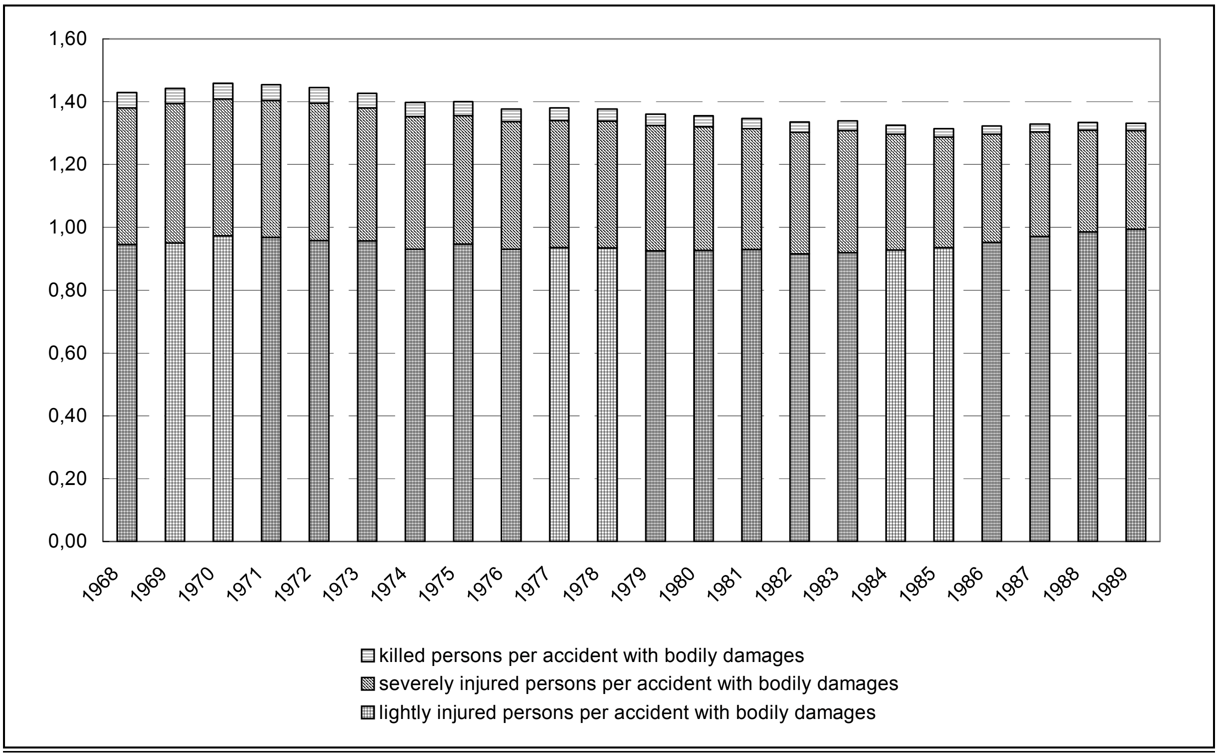
The morbidity and mortality rates are defined as:

- number of persons with light bodily damage (MBL) and with severe bodily damage (MBS) per bodily damage accident; they can be added (MB=MBL+MBS);
- number of persons killed per bodily damage accident (MO);

Graph 3.2. Structure of road accidents by category



Graph 3.3. Severity of road accidents by category



3.2.3 Matrix of direct effects

General overview: Table 3.1 shows the relationships between the dependent variables and the 12 categories of explanatory variables. In particular, note in the full list of Appendix 3.1 that:

- *exposure* was included with two variables derived from the dependent variables of road demand (KML and GCUI);
- *prices*: we used the real price of gasoline per kilometer, *i. e.* corrected for fuel efficiency, (RBPNSC) and the real price of diesel fuel per liter (RPBD) and the weighted combined price per liter (RPNSD);
- *quantity of motor vehicle*: this included the stock per employee for gasoline (PKWBPE) and diesel (PKWDPE) cars, for both their squared values as well;
- *characteristics of motor vehicles*: the belt usage rate was included (GAQC); this variable was corrected as observations started only in 1975 (with observed levels around 40%) so that we smoothed in earlier values with an geometric function;
- *laws, regulation and police surveillance*: this group includes the alcohol limit established in 1973 as a dummy (P08);
- *network and time service levels*: speed limits, especially those enforced during the time of the oil crisis (HHG and NHG7374), are included;

Table 3.1. Matrix of direct effects of SNUS-2.5

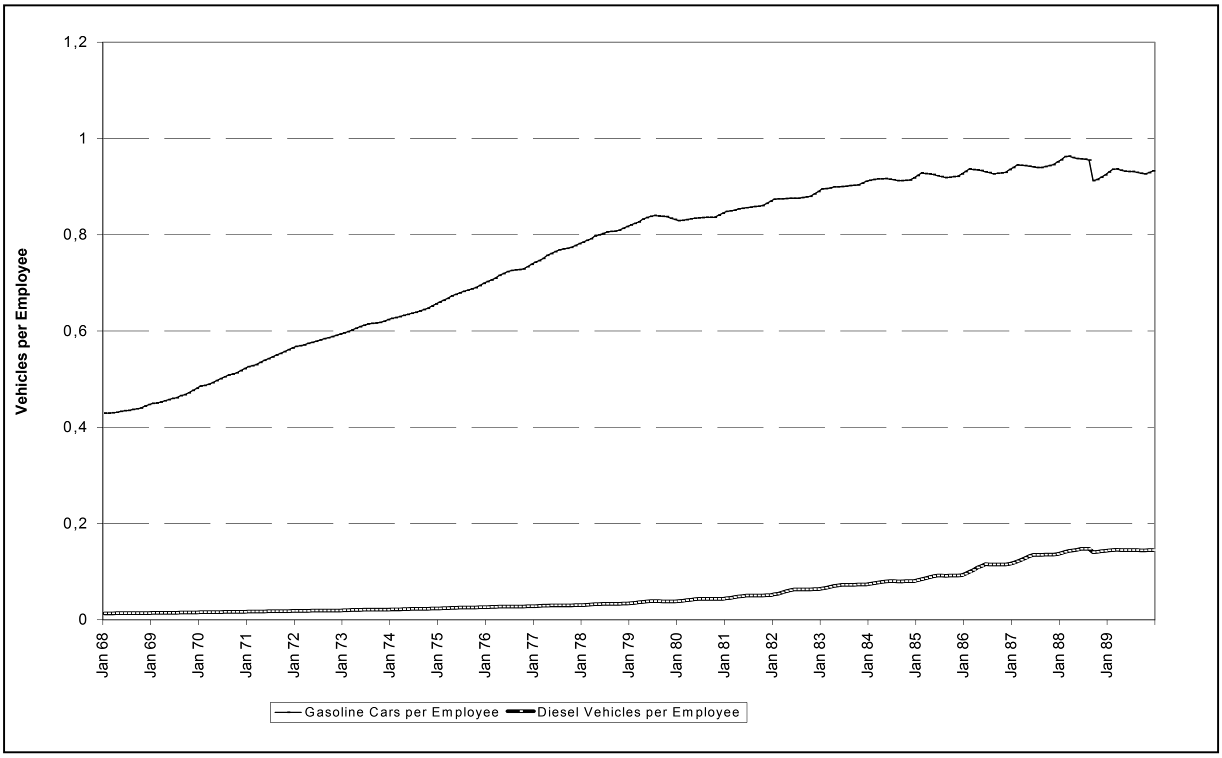
	Demand for road use (exposure)	Accident frequency	Accident severity	Victims
Exposure		√	√	D
Prices of fuel or other prices	√	√	√	D
Motor vehicle quantity and characteristics	√			D
Laws and regulations; safety measures	√	√	√	D
Network or time service levels of road modes	√	√	√	D
Infrastructure and weather	√	√	√	D
General driver characteristics		√	√	D
Ebriety or vigilance	√	√	√	D
Activities intermediate or final; income	√	√	√	D
Administrative		√		D
Aggregation, seasonal, trends	√	√	√	D

- *infrastructure and weather characteristics of the network*: four types of weather variables were used, and the city of Frankfurt was taken as a reference base for Germany, rainy days (RF) and precipitation (NIF), temperature (TFF) and sunshine (SSDF);
- *general characteristics of consumers*: these include the establishing of provisional driving licenses in 1987 (FSP);
- *ebriety or vigilance of consumers*: the level of retail sales in drugstores per adult (REUAERW) and the production of beer (BIERPE). This variable is more related to consumption than in the case of other alcoholic beverages, and is also used as an activity variable to model individual mobility;
- *final and intermediate activities*: final and intermediate economic activities play an important role for road use and were described by five variables. Besides long distance truck transportation (FVLKWPE), and sales and overnight stays per employee (REUNBPE, UENGPE), variables were constructed to capture the differentiated pattern of work attendance and free days in Germany. The complex holiday structure that varies among provinces is used to calculate an employee presence index and an index of free days (EPIFT, FRTMFG). Income does not play a role in the model once final and intermediate activities are accounted for;
- *et cetera with respect to administrative rules*: the change of the material damage classification after 12/82 was accounted for by a variable (SSSKIC) which was set to DM 1.000,- for the first 180 observations and DM 3.000,- for the observations thereafter. This series was then divided by the Consumer price Index;
- *et cetera with respect to aggregation*: as monthly data were used, the differences in the length of the months and the number of Saturdays, Sundays and holidays was captured with three aggregation variables (AT, ST, SF).

In practice, for reasons of multicolinearity, many of the variables were expressed in ratios, for instance per-employee ratios in the road demand functions or in per-km ratios in the accident and the severity models. Some variables of specific interest to Germany, and not shown in the discussion of results below, deserve comment: the stock of cars, the employment presence index and the sales in pharmacies.

Stock of cars and fuel efficiency: we clearly see in Graph 3.4 that vehicle ownership has increased tremendously over time with a tendency towards saturation in the gasoline fleet whereas diesel cars are still picking up. Germany was a latecomer in the private use of diesel cars.

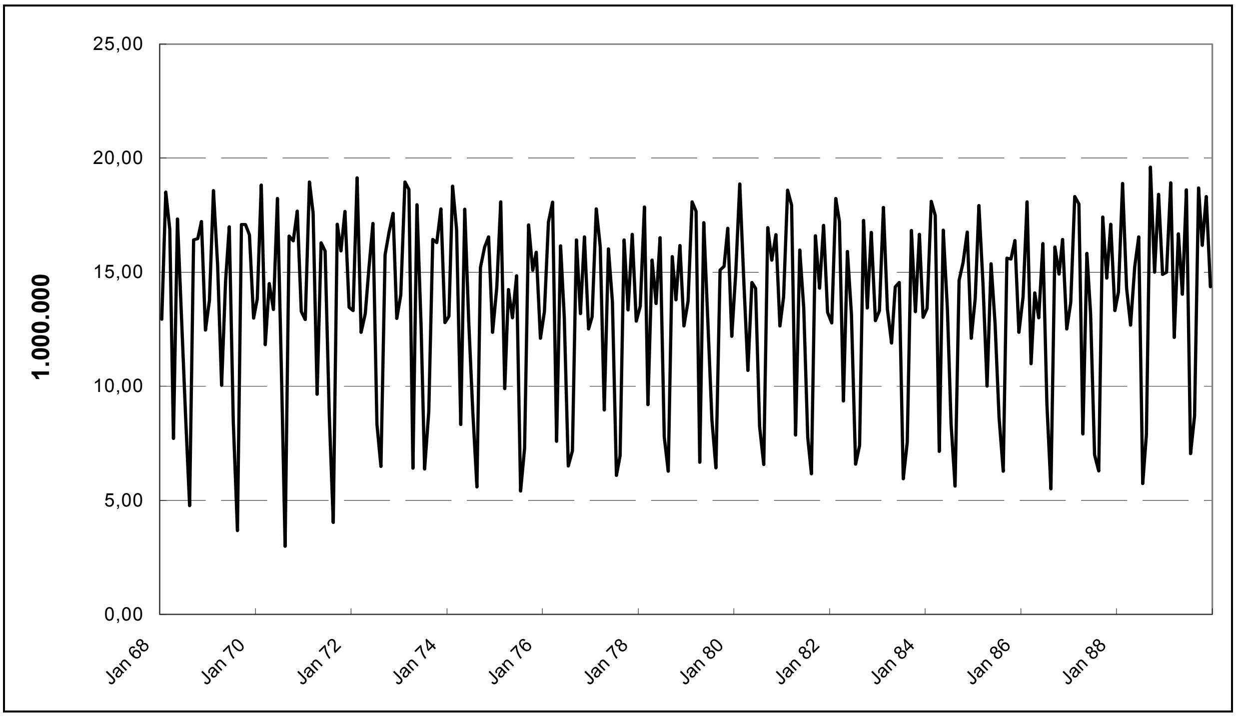
Graph 3.4. Vehicle ownership per employee in Germany



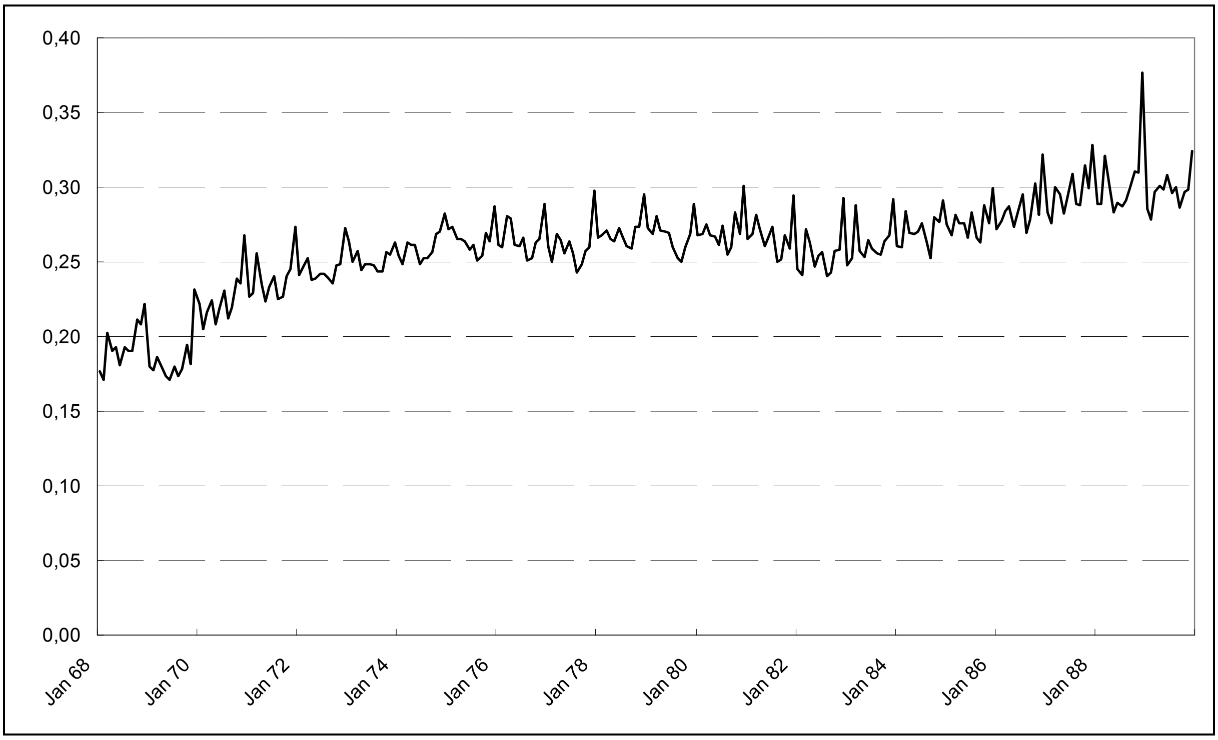
Employment presence: long term changes in German employment are rather small because of institutional regulations; their development over time is rather smooth and only has a limited explanatory variance. More important are fluctuations in worker presence because of the rather complicated holiday scheme in Germany where each province follows a distinctly different pattern, as shown in Graph 3.5. This is especially during summer where the six week school holidays of each of the provinces revolve over a time span of three months.

Retail sales in drugstores: in Graph 3.6 it is interesting to note both the strongly seasonal pattern of drug sales and the strong upper trend since 1982. The strong links with accidents and their severity shown in the Appendix imply increasing problems of management not independent from those requiring attention with an aging population. There is no age structure population in SNUS-2.5.

Graph 3.5. Employment presence index



Graph 3.6. Retail sales in drugstores per adult



3.3. Results and their interpretation

3.3.1 Statistical results

Each model is reported in a column of Appendix 3.1. The first two columns relate to road demand, columns 3 to 7 to the number of accidents and columns 8 to 11 to the severity of accidents. In seven out of the eleven equations, the same transformations was applied to the endogenous and all exogenous variables. In case of the remaining four, only one Lambda on all exogenous could be applied –a further breakdown did not provide any statistical gain. A strong heteroskedasticity could only be found in the case of the MBL equation.

Table 3.2. On functional form, stochastic specification, and other summary statistics

	Demand		Frequency					Severity			
	KMLB	KMLD	ULSS	USSS	USS	UPS	UG	MBL	MBS	MB	MO
X variables:	18	16	21	21	20	20	20	19	20	20	20
• n. of t-stat. $(2<t)$	10	6	10	12	8	13	10	6	8	6	5
• n. of t-stat. $(1<t<2)$	3	5	8	2	6	3	3	5	4	10	10
• n. of t-stat. $(0<t<1)$	5	5	3	7	6	4	7	8	8	4	5
Heteroskedasticity*	0	0	0	0	0	0	0	1	0	0	0
Autocorrelation **	9	2	4	5	4	5	4	5	5	5	4
Form											
• λ (y)	0,309	0,091	0,081	0,125	0,233	2,214	0,388	-3,198	0,973	-2,722	0,528
• λ (X_1)	0,309	0,091	0,081	0,125	0,233	1,200	0,388	0,947	2,183	0,276	0,528
• λ (X_2)	-3,296										
Significance											
• [LL at $\hat{\lambda}$ (opt)]	-3896,3	-4256,3	-2484,9	-2147,7	-2538,2	-2193,8	-2568,9	737,6	901,0	789,7	1219,4
• [LL at λ=1(lin.)]	-3916,1	-4311,8	-2515,6	-2209,0	-2556,9	-2206,9	-2575,7	708,5	898,4	781,6	1214,2
• [LL at λ=0(log.)]	-3908,4	-4264,2	-2485,4	-2149,0	-2540,0	-2240,1	-2574,3	712,6	892,4	784,1	1211,7
Sample (1/68 – 12/89)	264	264	264	264	264	264	264	264	264	264	264

* number of parameters ** number of rhos

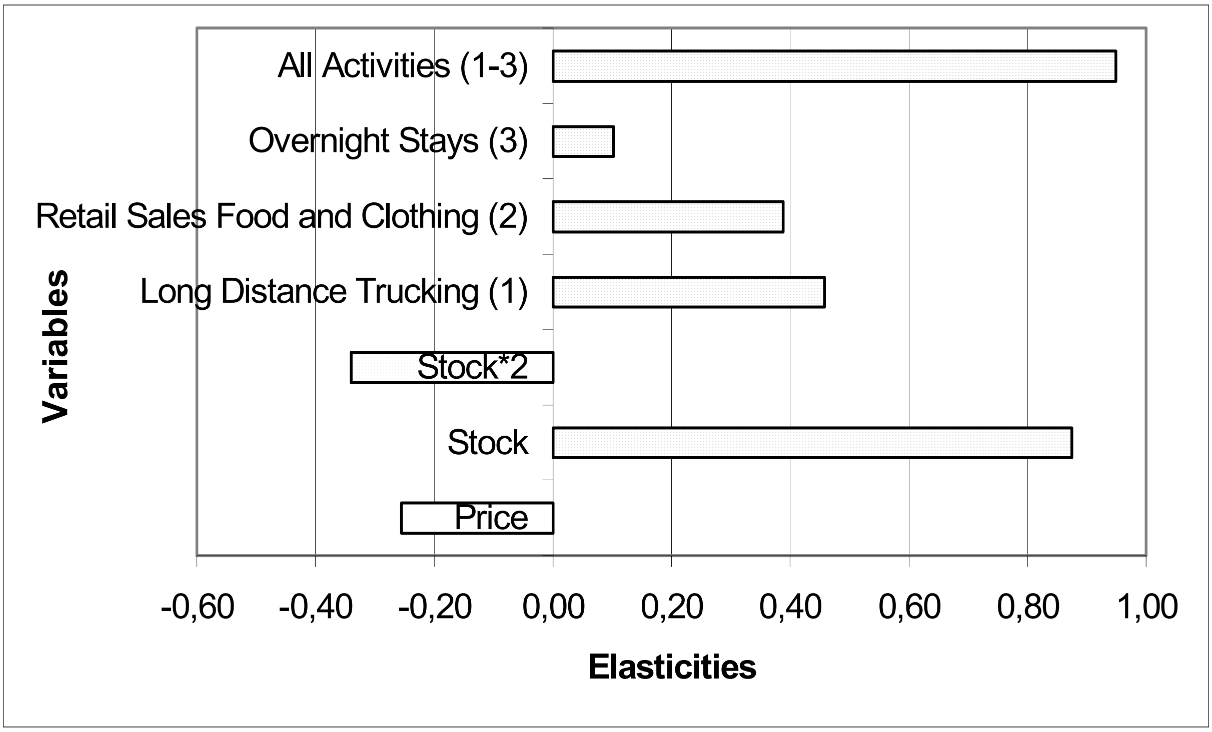
Autocorrelation of multiple orders was present in all of our series – in all of our equations, a first order was found, a strong autocorrelation structure around orders 4 and 11/12. All R^2 are very high. Multicollinearity was eliminated using the BELSLEY test by excluding affected variables or expressing them as ratios. We also summarize in Table 3.2 the overall results. It is easy to see how models with fixed forms would not have been acceptable.

3.3.2 Economic results: overall specific results

Road demand. Figures 3.1 and 3.2 summarize important results not discussed in detail below. If we analyze the impact of the gasoline and the diesel fleets, we see that additional cars first increase and later decrease road demand, i.e. the structure of the quadratic function is concave.

The case of the diesel vehicles involves a straightforward quadratic form with coefficients $\beta_1=81{,}6 > 0$ and $\beta_2= -357{,}5 <0$ describing a maximum at *0,114* vehicles per employee, which is well above the average of that series (*0,06*) – in fact, this maximum was surpassed only from June 1986 onwards. To understand how additional diesel cars could reduce demand it has to be remembered that the dependent variable is a transformation of liters into kilometers that does not take into account the increased fuel efficiency of the diesel engine and that additional vehicles are often small cars.

Figure 3.1. Decomposition of road demand (diesel) by important variables

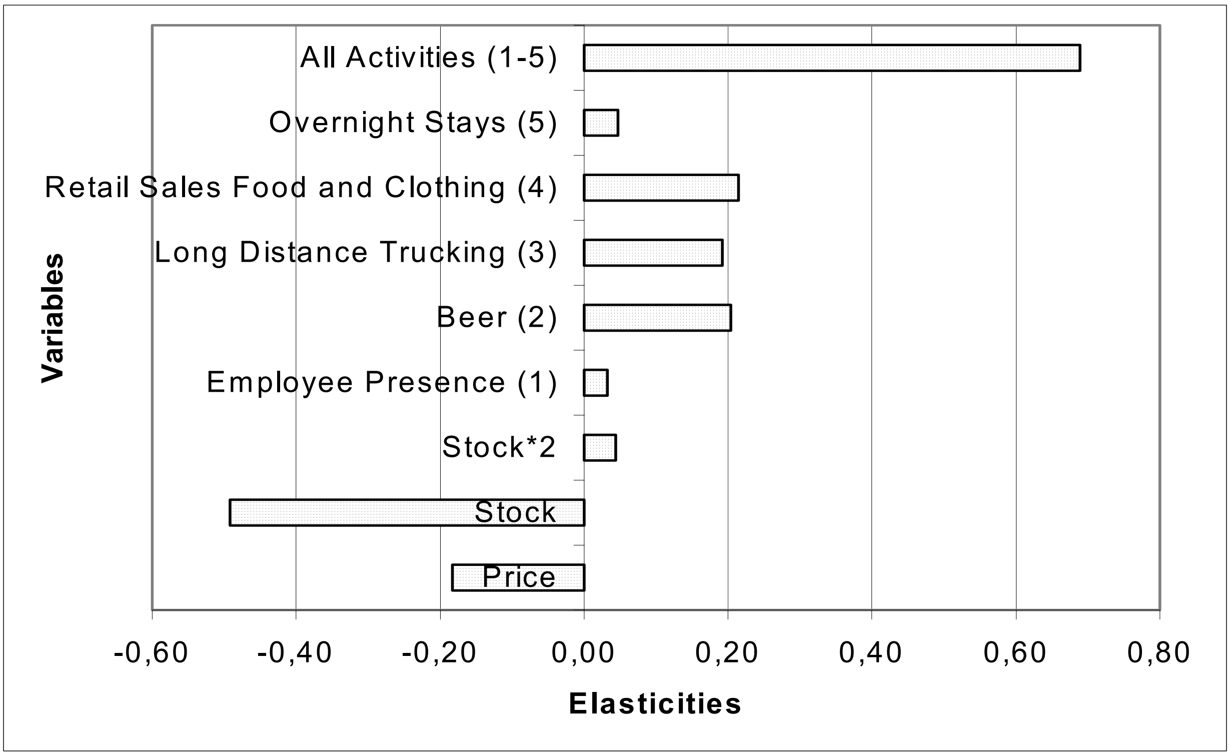


As for gasoline cars, the function used[2] involves $X^{(\lambda)}$ and $\left(X^2\right)^{(\lambda)}$. It can be shown (GAUDRY and BLUM 1999) that a maximum occurs if

$$\beta_1 \cdot (\lambda - 1) \cdot X^{\lambda - 2} + 2 \cdot \beta_2 \cdot (2 \cdot \lambda - 1) \cdot X^{2 \cdot \lambda - 2} < 0,$$

a condition that is met in our case with coefficients $\beta_1 = -93 > 0$ and $\beta_2 = 4,4 < 0$ because of the hyperbolic transformation with $\lambda = -3,3$ describing a maximum at $x = \left[-\beta_1 / 2 \cdot \beta_2\right]^{-\lambda} = 0,49$ cars per employee. This maximum, however, lies well below the average of *0,800* cars per employee —the maximum was surpassed from April 1970 onwards.

Figure 3.2. Decomposition of road demand (gasoline) by important variables



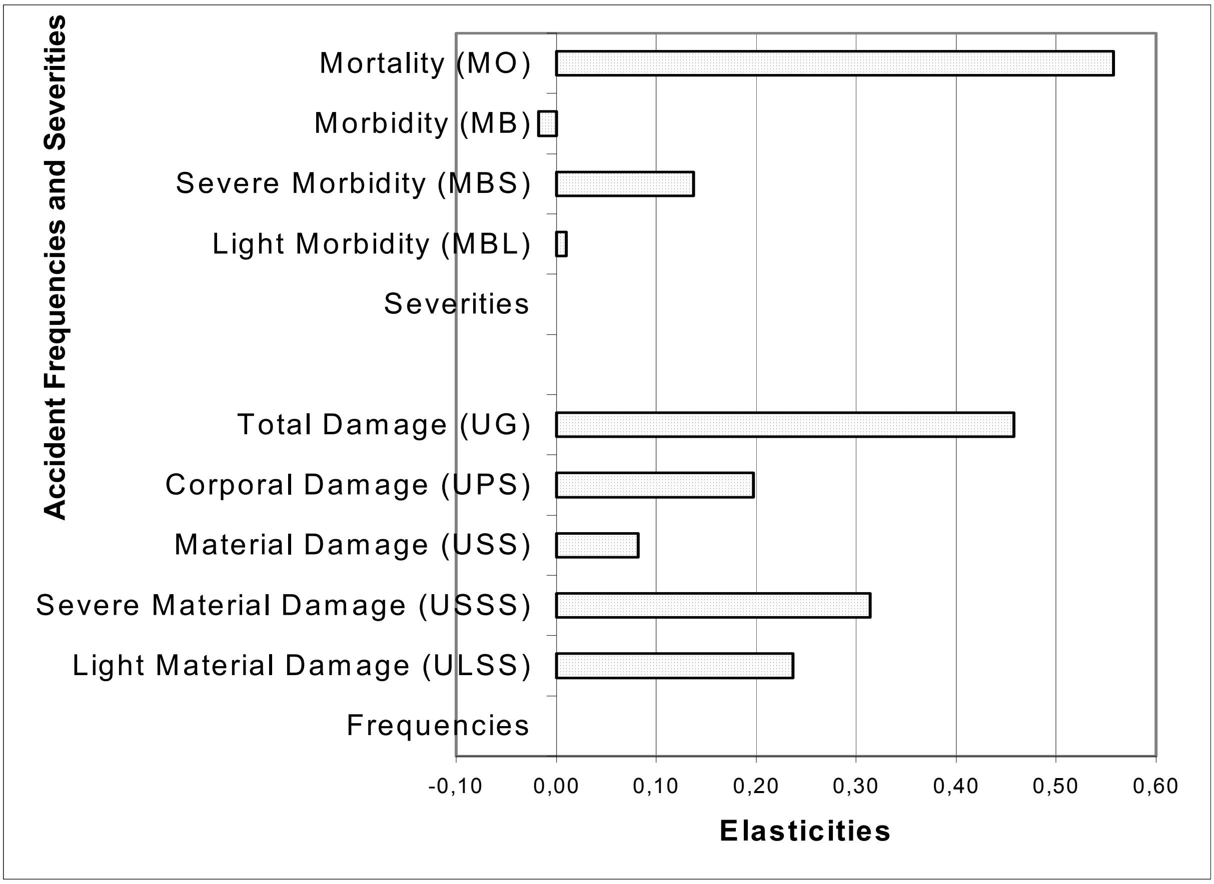
This means that, in both the diesel and the gasoline vehicle stock cases, marginal additions are associated with reduced kilometrage. Further work is needed to understand the extent to which unmeasured congestion and population aging contribute to this result, in addition to factors already mentioned.

[2] The addition of the squared term and the use of a λ specific to both increased the log-likelihood from *–3900,08* to *–3896,33*. In the above-mentioned diesel equation, an attempt to use a similar form yielded $\lambda = 0,915$ and demonstrated that the simple quadratic form term used was sufficient.

3.3.3 Decomposition of the impact by variable: results common to other models

Exposure: Exposure, shown above on Graph 3.1, has differentiated impacts, as shown in Figure 3.3. As an endogenous variable in the accident frequency models, we see increased impacts on severe material damage, and a shift to higher risks in the severity models.

Figure 3.3. Impact of exposure on road accidents



Fuel price: The evolution of fuel prices is shown in Graph 3.7, and the impact of the two (combined) prices on accident frequency and severity shown in Figure 3.4 is of major interest as it implies an inference on risk taking of higher prices despite relatively low elasticities of the demand for road use itself.

Graph 3.7. Real Prices of Fuel

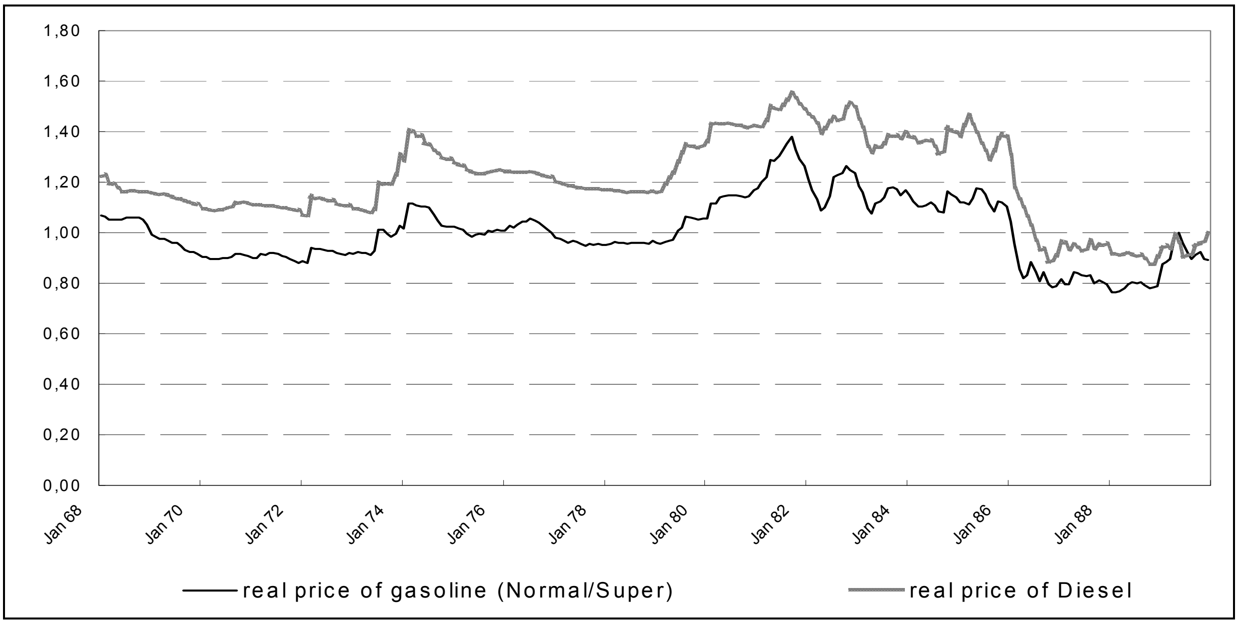
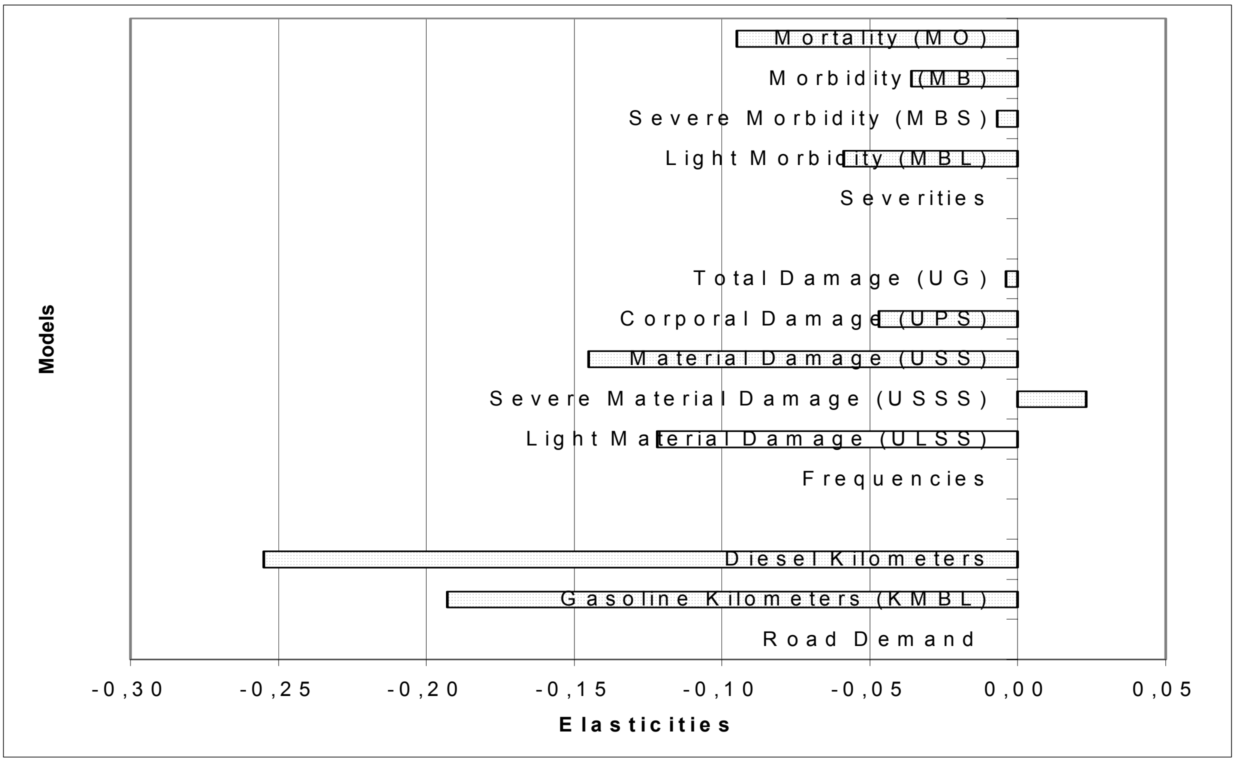
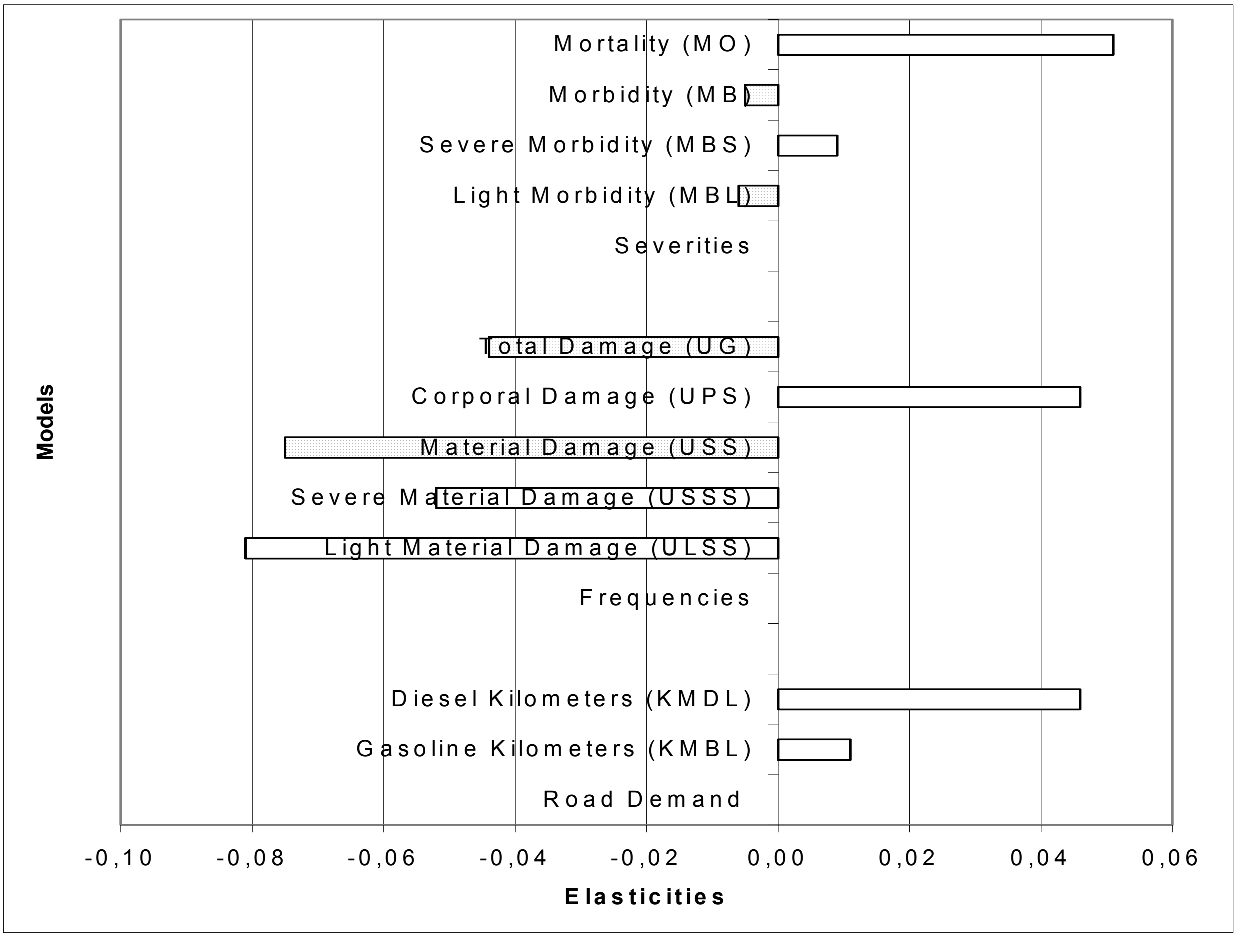


Figure 3.4. Impact of fuel prices on road demand and road accidents



Temperature: As shown in Figure 3.5, rising temperatures imply strong decreases in material damage accidents and strong increases in the frequency of bodily injury accidents and in morbidity and mortality rates, to say nothing of the strong increase in road demand.

Figure 3.5. Impact of temperature on road demand and road accidents



Percentage of belt use: Figure 3.6 indicates that belt use reduces both the frequency and the severity of bodily injury accidents, increasing the frequency of material damage accidents.

Beer consumption: as shown in Figure 3.7, beer consumption is both a social activity variable, thereby increasing road demand, and a factor changing the frequency and severity mix of accidents, but the effect on the increase in bodily injury accidents is larger than that on mortality, implying an increased number of fatalities. Our results are consistent with the view that most of those that drink and drive have only consumed little and compensate to prevent accidents, while those who drink a lot may increase their risk.

Figure 3.6. Impact of belt use on road accidents

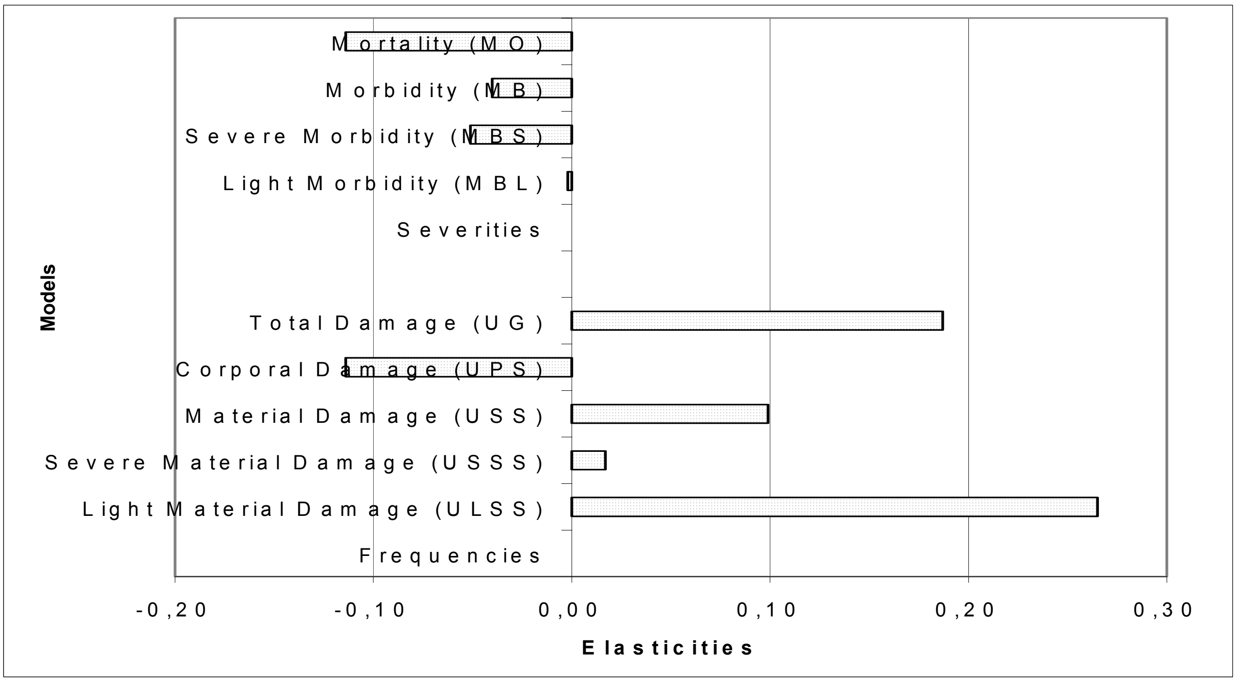
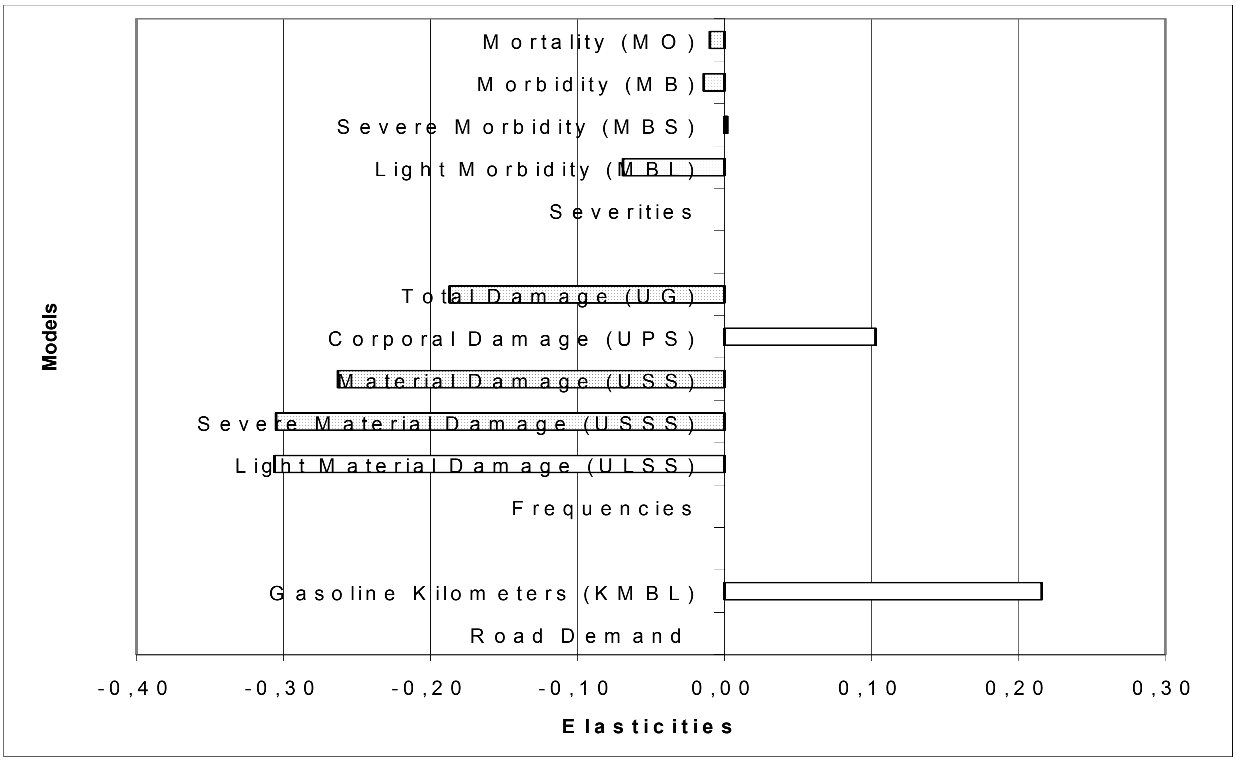
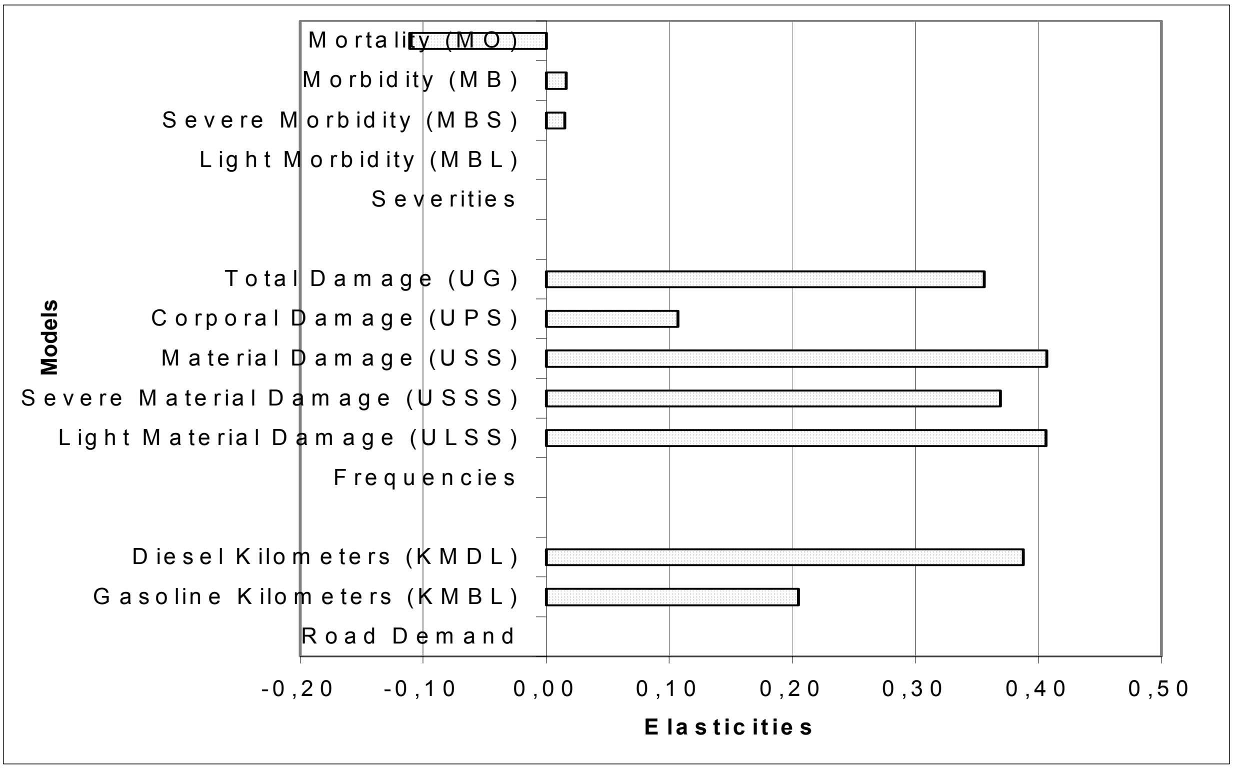


Figure 3.7. Impact of beer consumption on road demand and road accidents



Food and clothing: Figure 3.8 shows that shopping trips are relatively dangerous, perhaps because this trip purpose involves higher occupancy rates of vehicles than, say work trips, thereby increasing the frequency of bodily injury accidents three times as much as that of material damage accidents; these effects are not fully offset by reduced mortality rates.

Figure 3.8. Impact of demand for food and clothing on road demand and road accidents



3.3.4 Results for other variables

Sunshine: As shown in Figure 3.9, the effects of sunshine on the frequency and the severity of accidents are startlingly strong. It may be that sunshine reduces visibility in ways that are insufficiently compensated by drivers.

Rainy days and precipitation: Figures 3.10 and 3.11 show the distinct but closely related effects of the presence of rain and of the amount of rain per day. Including both variables in the model allows us to account for distributive effects of rainfall over the month, but the presence of rain has larger proportionate impacts than the amount of rain.

Figure 3.9. Impact in sunshine on road demand and road accidents

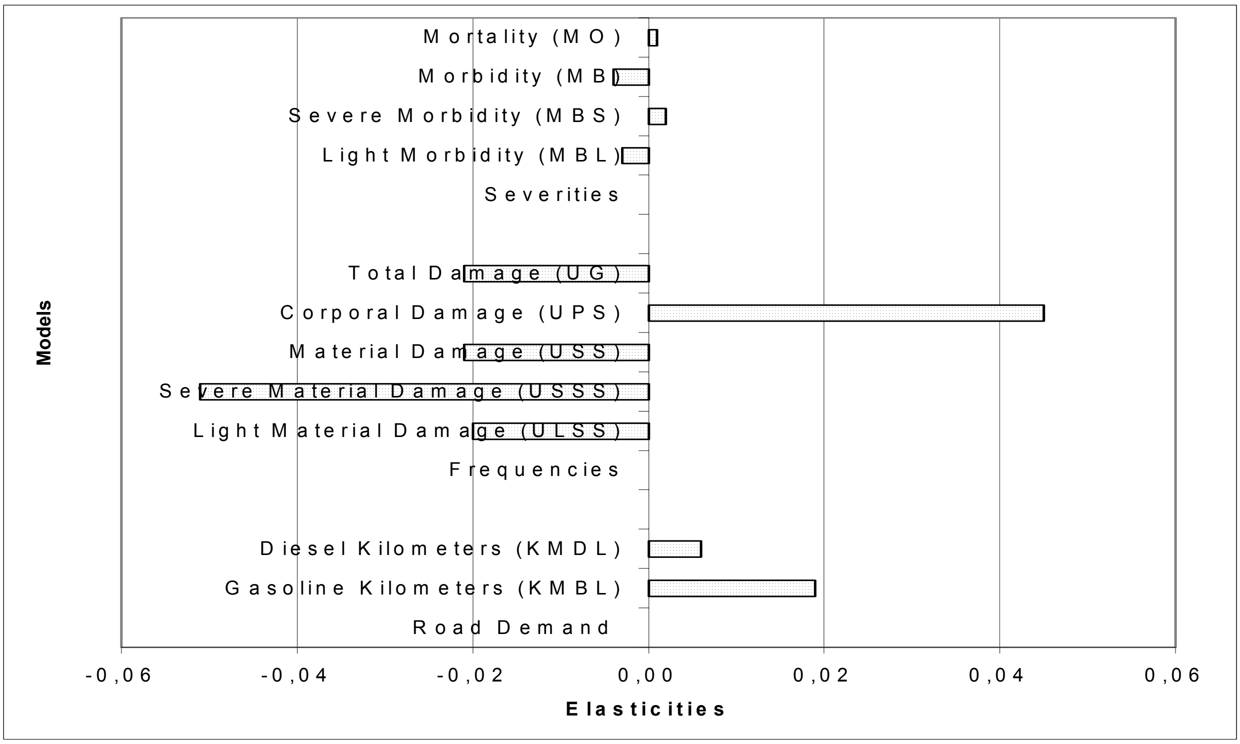


Figure 3.10. Impact of rainy days on road demand and road accidents

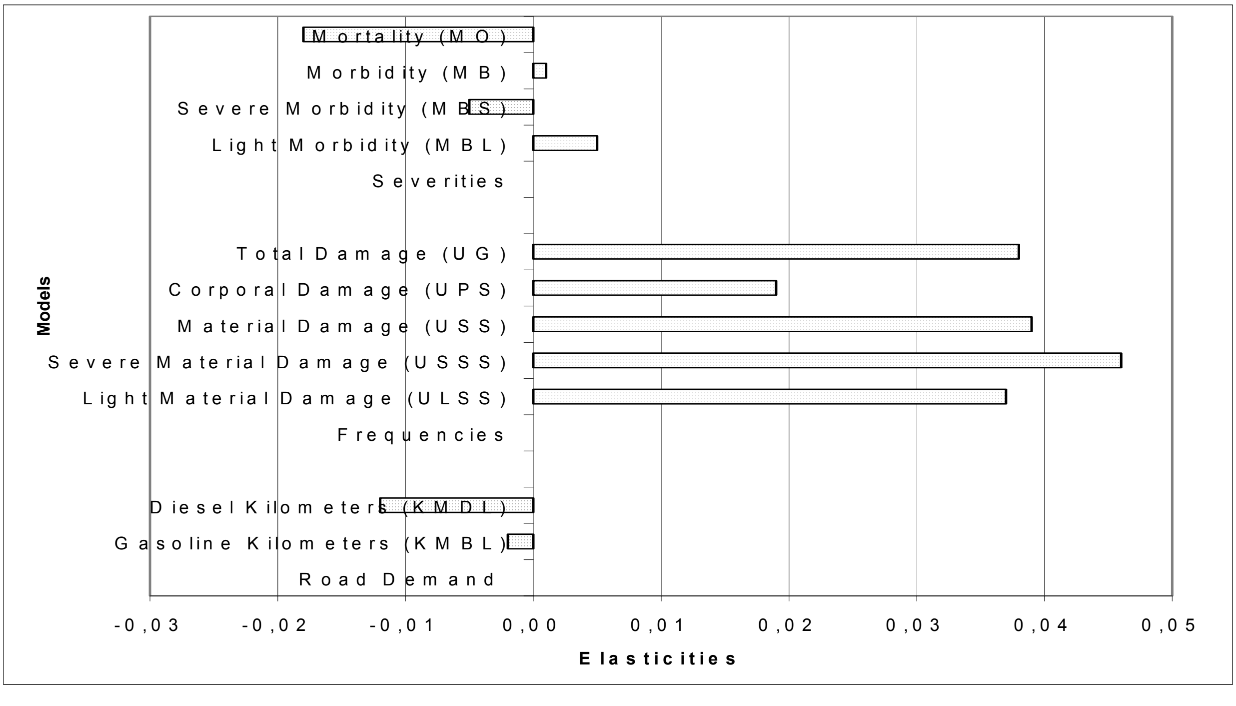
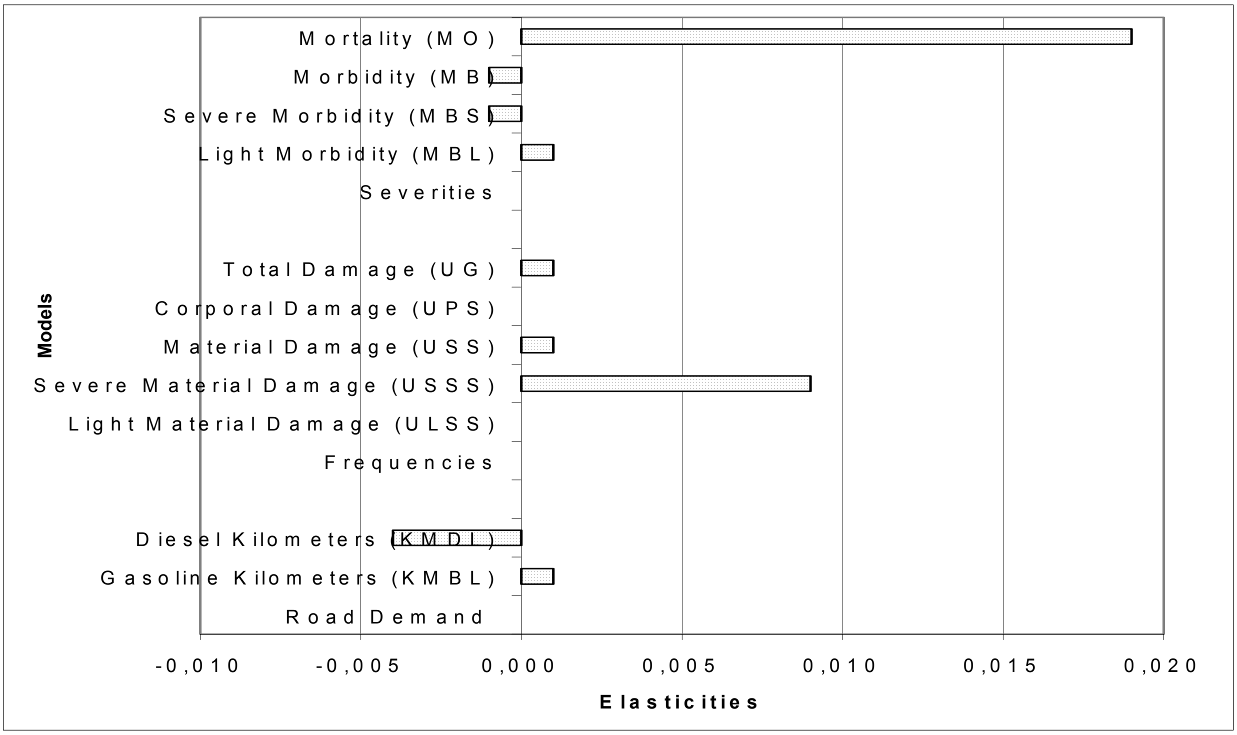


Figure 3.11. Impact of mm of rain on road demand and road accidents



Speed limits 1973-1974: as shown in Figure 3.12, the imposition of speed limits in the aftermath of the October 1973 first oil shock had beneficial effects on all dependent variables.

Blood alcohol limit imposed in 1973: it is clear in Figure 3.13 that the 0,8 % blood alcohol concentration (BAC) limit imposed on October 1, 1973 reduced driving, accidents and their severity.

Retail Sales in Drugstores: In passing, we note that accident risks are heavily polarized because of significant increases of light morbidity and of mortality rates.

Figure 3.12. Impact of 1973-74 speed limits on road demand and road accidents

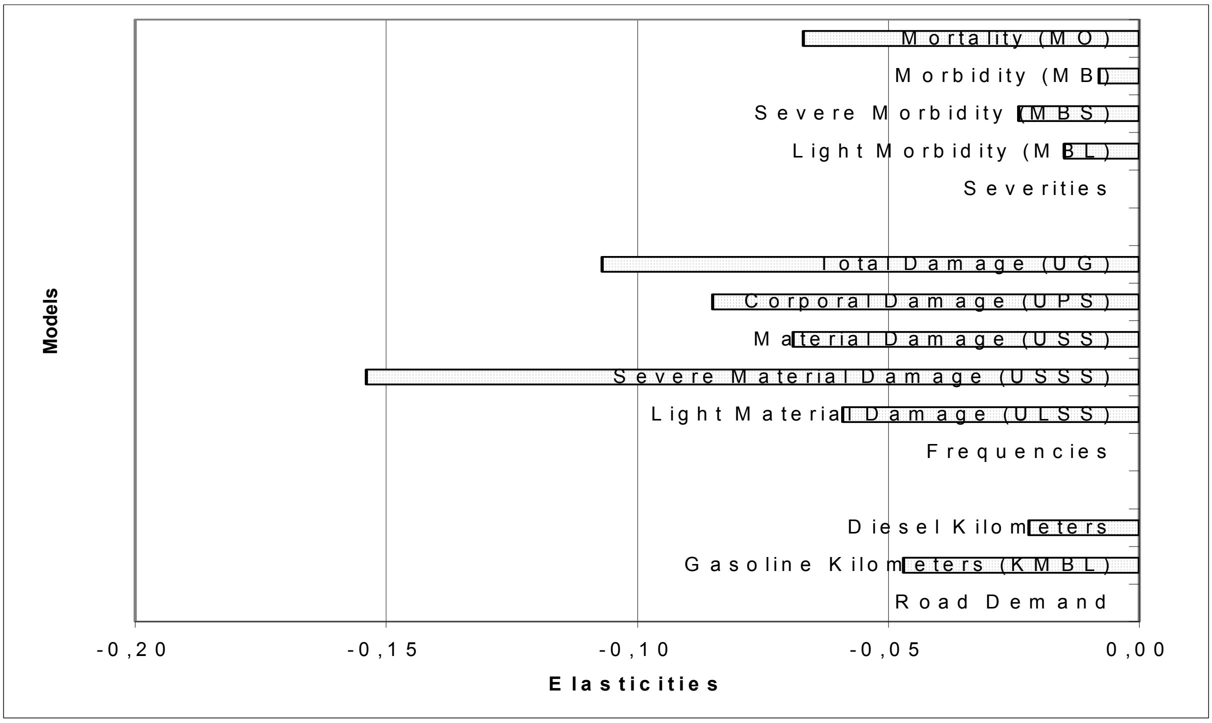
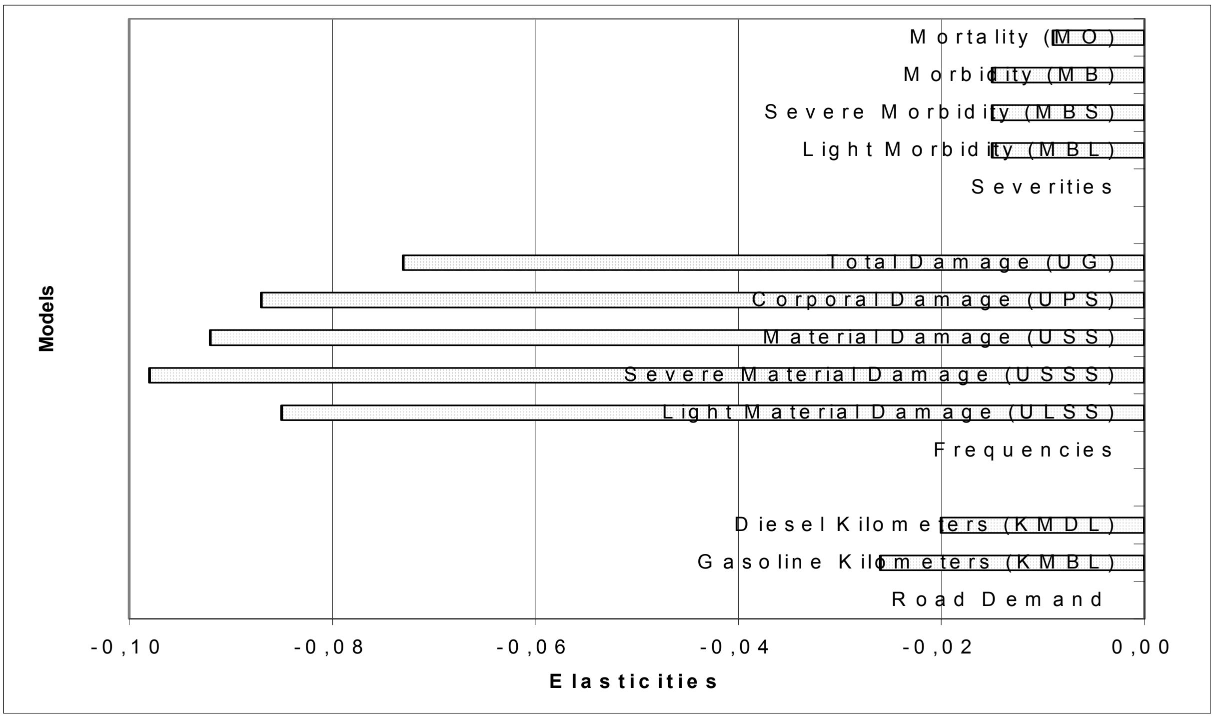


Figure 3.13. Impact of blood alcohol limit on road demand and road accidents

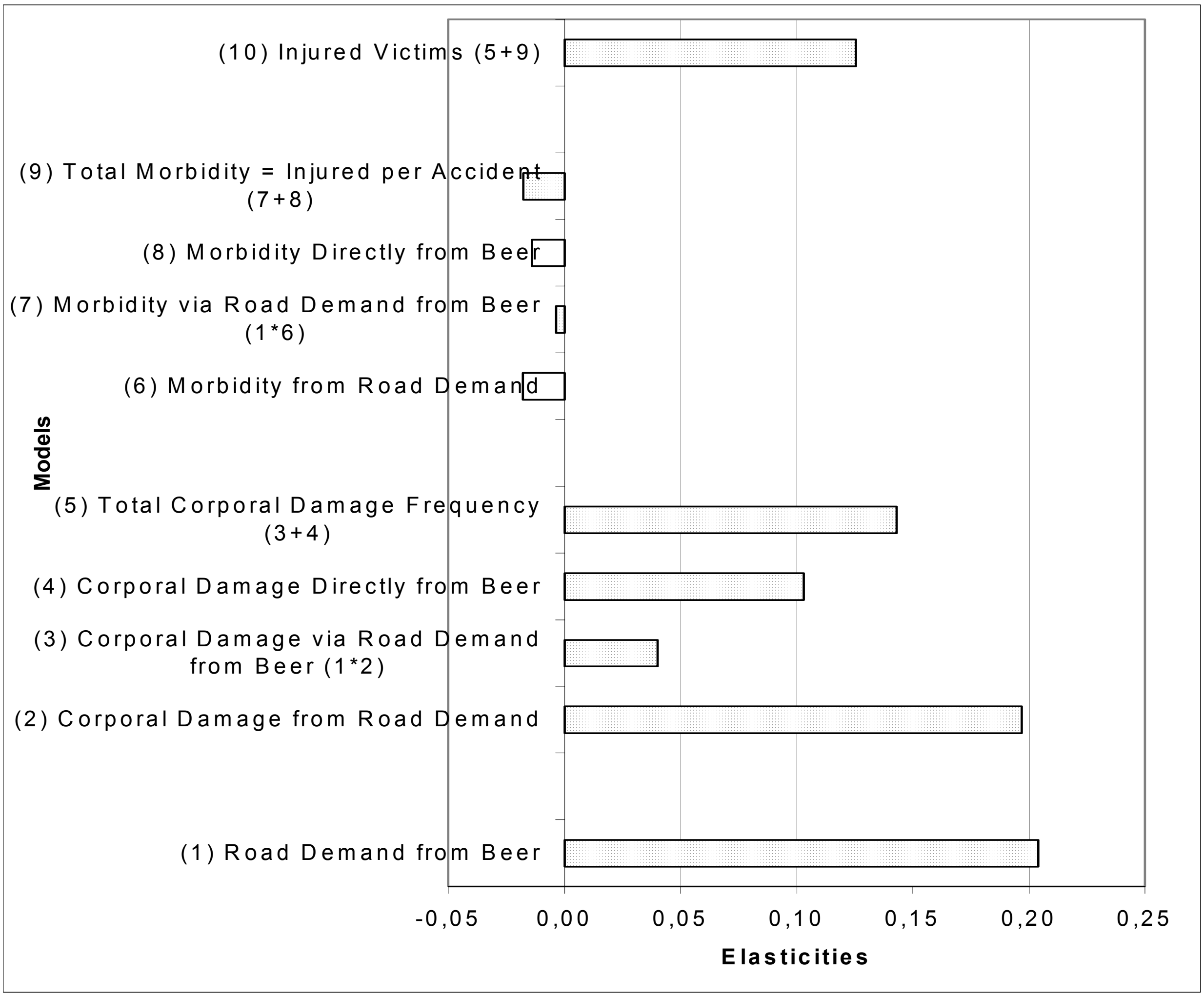


3.4. Deriving other interesting results

3.4.1 The analysis of victims: direct, indirect and total elasticities

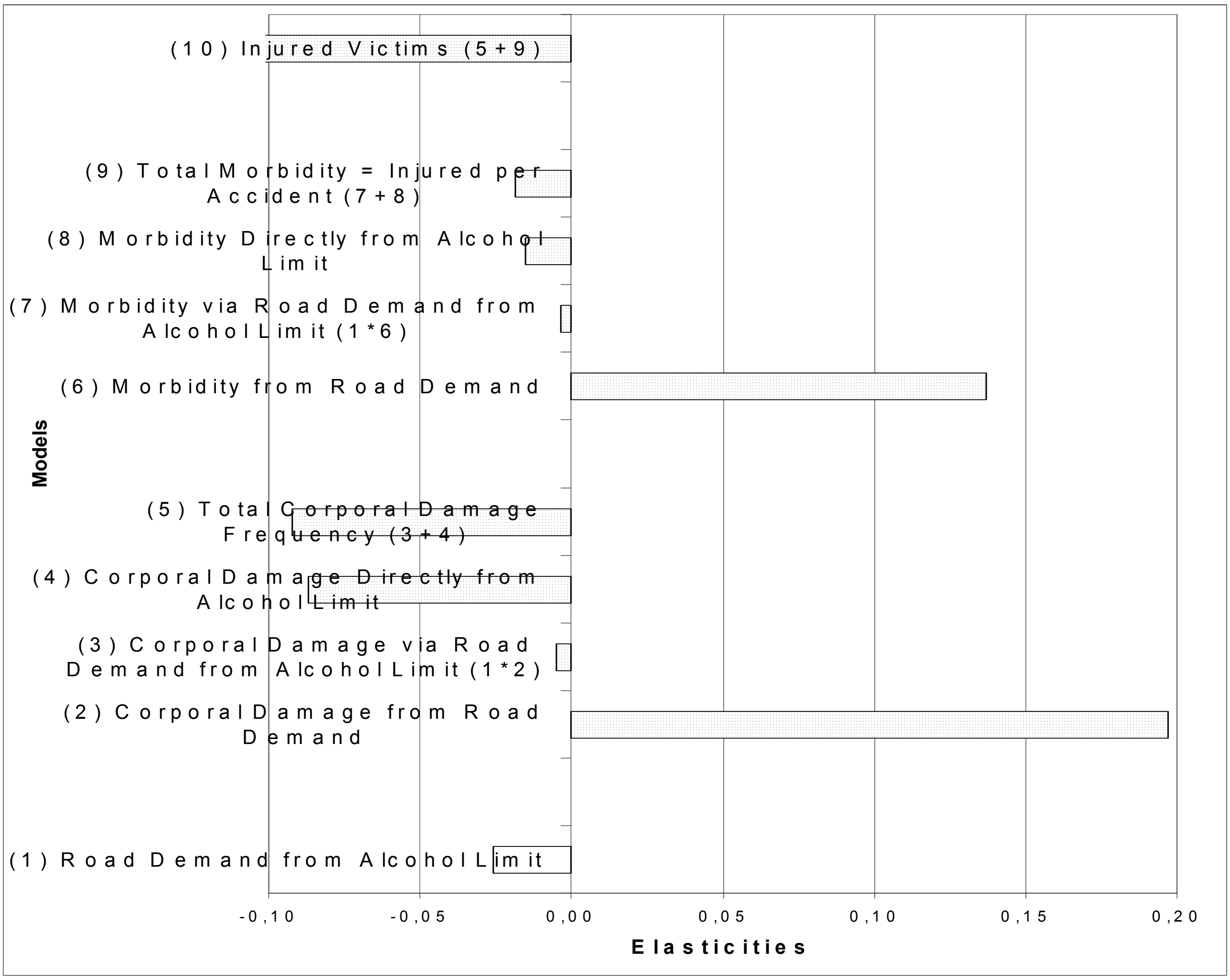
The inquiry into victims will first concentrate on the impact of alcohol; all other variables can be analyzed in the same way. We will derive the impact on injured persons of both changes in beer consumption and BAC limits, taking due account of the indirect effects rippling from the demand equation to the frequency and the severity equation. Finally, we will add a corresponding analysis of the impact of fuel price.

Figure 3.14. Direct, indirect and total corporal impacts of beer consumption



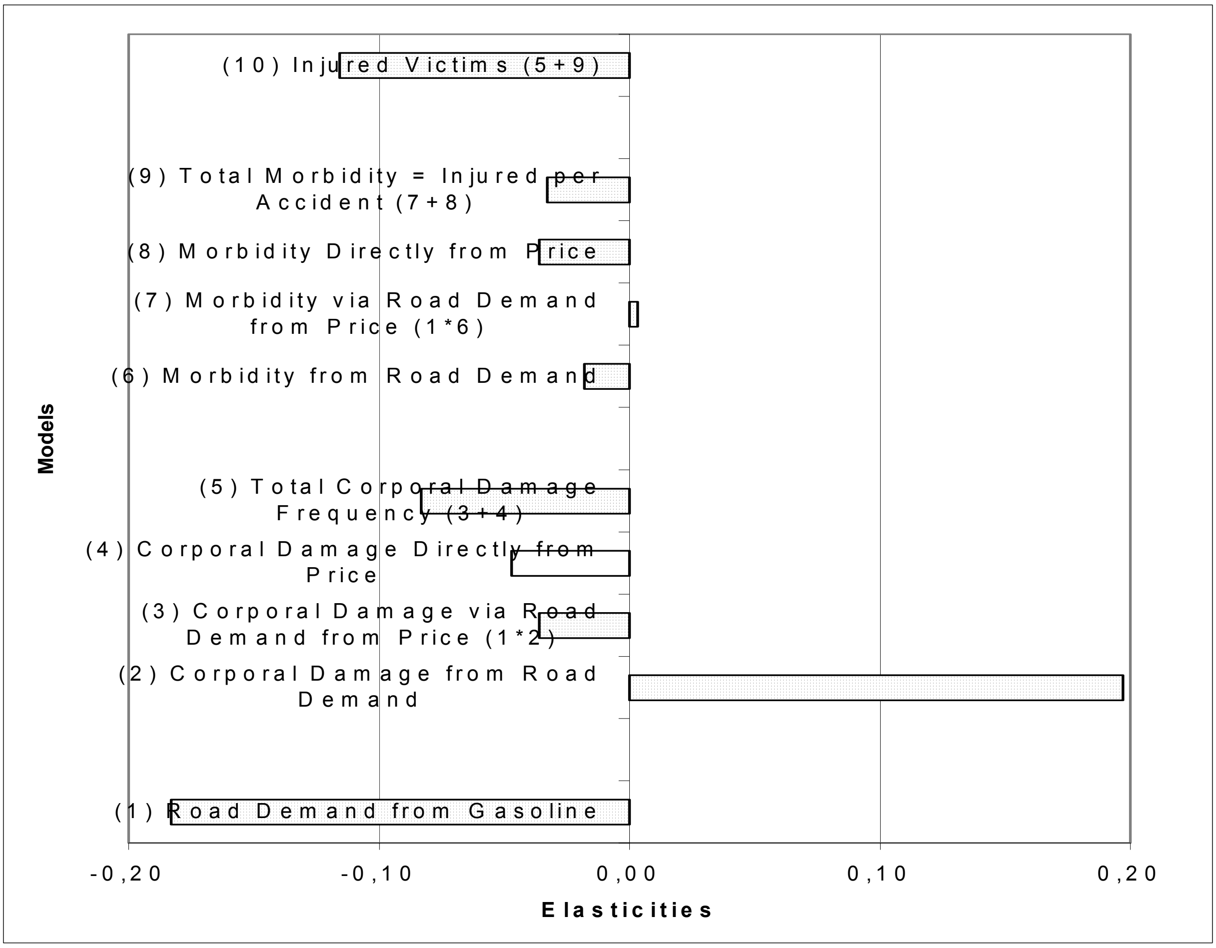
Let us then determine how the change of one exogenous passes through the different layers of the model. Take, for instance, beer consumption in Figure 3.14: it increases road demand (elasticity of *+0,204*) and road demand increases corporal damages (*+0,197*), giving a total effect of *0,0402*. The direct effect of beer consumption on corporal damage frequencies is *0,103*, so it adds up to a gross corporal damage frequency elasticity of *0,1432 (= 0,0402 + 0,103)*. Furthermore, given the impact of beer consumption on road demand (*+0,204*) and of road demand on morbidity (*-0,018*), the total indirect effect is *-0,0037*; accounting for the direct effect of beer consumption (*-0,014*), we obtain a total morbidity (i.e. injured per accident) of *-0,0177 (= -0,0037 - 0,014)*. The total elasticity for victims is the sum of the total frequency and morbidity elasticities, i.e. *0,1255 (= 0,1432 - 0,0177)*.

Figure 3.15. Direct, indirect and total corporal impacts of the alcohol limit



These derivations are indicated in Figure 3.14 for beer consumption, in Figure 3.15 for the August 31, 1973 blood alcohol concentration limit, and in Figure 3.16 for the gasoline price. The interested reader can compare in these graphs the direct effects, the indirect and the total effects.

Figure 3.16. Direct, indirect and total corporal impacts of the fuel price



3.4.2 Multiple moments and their marginal rates of substitution

Observations and moments. All discussions above focus on « explaining y ». But if drivers are trying to achieve a combination of risk objectives through control of y, observations on y are just about the tool, about a sort of derived demand, that should reveal an underlying mechanism at work. In the analysis of financial returns of assets, for instance, it is believed that at least the first and second moments of y (return) are of interest to investors. But the introduction of such a wedge between « explaining observations » on a variable and « explaining moments » of that variable in effect constitutes a major change, both conceptually and in terms of required computations.

Firstly, except in a linear model, « explaining y » is not the same as « explaining μ (y) », the first moment or expected value of y, even if this distinction is ignored in conversation. More generally, if drivers care about many features of the occurrence of accidents, and in effect care about the very shape of the accident probability distribution, then regression models should be constructed, and their measures of « quality of fit » defined, not just in terms of « observed y », although this remains of some interest, but in terms of the first moment and of higher moments : the moments of y themselves have become the objects of explanation. This requirement is a tall order for model specification because intuition about road safety is generally only about the first moment (the expected value) and only about accident frequency (not about severity rates). In consequence, model building is, at best, implicitly oriented towards fitting only the first moment : to be more precise, it is usually explicitly oriented only towards fitting the « observed y»—and towards interpreting the results in terms of that single dimension. It is also a tall computational order to obtain all derivatives, elasticities and marginal rates of substitution pertaining to all moments of y. For instance, discrete choice models are not yet concerned with densities of the choice probabilities because the task is extremely difficult.

Moments, utility maximisation and local trade-offs. Clearly, as observed accident frequency distributions are not normal (Gaussian), there would be an *a priori* case for thinking that an underlying multimoment mechanism seeking « desired » values in moments is at work. The moments of interest, in addition to the first, should include the variability of the accident probability, as measured by its variance (or, more conveniently, by the standard error σ (y)), and whether the accident risk is skewed « downwards » or « upwards », as measured by α (y), the asymmetry coefficient (that can be negative (to the left) or positive (to the right)). The fourth moment, kurtosis, that tell us about the concentration of observations, its « flatness » or « peakedness » about the mode of the distribution, might also be of eventual interest. But the nature of the underlying utility function is difficult to hypothesise with moments higher than the second and dubious even for the second because implied quadratic utility functions are not without their problems, well summarised in MACHINA and ROTCHSCHILD (1987).

The theory of expected utility used in financial analysis, for instance the well-known capital asset pricing model (CAPM), allows expected utility to depend only on two such moments because nobody really believes that the mathematical expectation of asset return is the only moment that matters to utility. In consequence, the usual investor with positive marginal utility $\left[\partial U/\partial w \rangle 0\right]$ of wealth w, diminishing as wealth increases $\left[\partial^2 U/\partial w^2 \langle 0\right]$, has long been shown to display positive preference direction for the first moment and negative preference direction for the second moment. But the formalization of underlying mechanisms, and the measurement of trade-offs or marginal rates of substitution among moments, has proven very difficult for moments higher than the second. Although KRAUS and LITZENBERGER (1976) have implied positive preference direction for the normalized third moment and SCOTT and HORVATH (1980) appear to have shown more generally that the investor's preference direction is positive (negative) for positive (negative) values of every odd central moment and negative for every even central moment, these results have recently been thrown into doubt by BROCKETT and GARVEN (1998) who have constructed counterexamples showing that this convenient rule of preference direction is false and that the *ceteris paribus* conditions assumed by these demonstrations are logically impossible since equality of higher order central moments implies the total equality of the distributions involved.

In view of this last result that, for any commonly used utility function, moment preferences do not match up with a sequence of expected utility derivatives, we adopt the simple-minded view that *observed choices reveal underlying local utility trade-offs* and that it will eventually be possible to construct acceptable analytical mechanisms of utility maximisation consistent with them.

Moments in accident analysis. Analyses of road safety treating accidents of various categories as a portfolio took a long time to appear. Despite the intuitive appeal of this view, we are not aware of any published accident moment studies outside of the DRAG research network. In other domains of application, such as the analysis of political events, formal statistical concerns with overdispersion and underdispersion within the Poisson model (KING 1989) are relevant, for the two-moment case at least, but do not formally treat the accident probability as a two-moment trade-off problem.

Within the DRAG network, formal calculations (partial derivatives and elasticities) of observed y, μ (y) and σ (y) are fully documented and available in the Tablex tables of TRIO since 1993 : the computations are not trivial, for equations (1) to (3) with Box-Cox transformations, heteroskedasticity of a general form and multiple-order serial autocorrelation. Two-moments tests of derivatives, elasticities and of rates of substitution (also called ALLAIS' r (ALLAIS, 1987) coefficient) using these program features had started in 1990-1991 and had been duly reported to the funding agency (SAAQ, 1991) and at various seminars in 1993 and 1994 on the basis of DRAG-1 results (presenting in particular effects of the snowfall variable). But the first generally available manuscript on these two-moment tests (presenting in particular effects of the temperature variable), written after a long, and perhaps unnecessary, wait for the longer series (481 observations, instead of 313) DRAG-2 results produced in 1997 to generate forecasts (FOURNIER et SIMARD, 1999), was completed only recently (GAUDRY, 1998).

That paper shows the fitted implicit trade-offs or marginal rates of substitution between the expected value μ and the standard error σ of accident frequencies, severities and victims by category, as well as the cross-category trade-offs among the accident frequencies of DRAG-2. The estimates turned out to be extremely close to those of the DRAG-1 model, despite the vastly increased sample size (481 instead of 313 observations) of the most advanced model. Also, the very reasonable values found implied a rejection of a Poisson assumption for all equations but one : the Poisson assumes that the first two moments of a dependent variable are equal, so that that the marginal rate of substitution between a unit of expected value and a unit of variance is one. There is of course no reason why behavioral rates of substitution among moments of a given dependent variable should be so restricted in accident analysis, or elsewhere for that matter.

From two to three moments : more locally revealed trade-offs. Here we want to extend the analysis to the third moment α, called asymmetry, having augmented the 1993 algorithm previously limited to the first two moments. As α is adjusted by division by the third power of σ, it is without dimensions and can naturally be positive or negative, according to whether the distribution has a tail to the right or to the left : by convention, this distribution is said to be « noticeably skewed » if α is greater than one-half in absolute value. We therefore extend to the third moment the hypothesis that drivers *do locally adjust separately and independently (in non-Poisson fashion) among the moments of accident frequencies by category, and across categories*. Their utility simply depends on the mathematical expectation, standard error *and* asymmetry of the accident probability : with revealed local trade-offs, it should be possible to construct certainty equivalence measures expressing these risk dimensions in terms of a *numéraire* about which it is meaningful to inquire whether drivers maintain it at a constant « homeostatic » level or not.

Germany, Quebec and speed limits. To perform our multimoment analysis, we limit ourselves to a discussion of frequencies and neglect other levels of the model structure, such as severity, due to the large amount of information to be reported and to the importance of making a comparison of Germany with Quebec. We compare both the data and the results of SNUS-2.5 and DRAG-1 accident frequency equations, as these models contain a common 15-year period, 1968-1982, within their respective longer monthly time series samples. A crucial difference between these data sets pertains to speed limits : there is no speed limit on more than three quarters of the 12 000 km German autoroute network. As compared to a fully regulated network, this « high end» freedom should affect trade-offs, both among moments of a given accident category and by implication across accident categories, for accidents most likely to occur at high speeds. It has been noted (PRAXENTHALER, 1987) that, over the period 1970-1986, both the auroroute share and the autoroute frequency per vehicle-kilometre (relative to the frequency for the total German road network) of injury accidents increased.

Trade-offs and units. The marginal rates of substitution among moments, defined as ratios of partial derivatives of moments of y with respect to independent variables X_k, do not depend on the variable considered : $\left[\partial(\text{mom. i})/\partial X_k\right]/\left[\partial(\text{mom. j})/\partial X_k\right] = \partial(\text{mom. i})/\partial(\text{mom. j})$. They are indeed the same for all independent variables of an equation—even though the partial derivative of any moment with respect to a particular independent variable (say snow or temperature) naturally depends on the variable considered. Note however on this point that, given the derivative with respect to the first moment, $\partial\mu/\partial X_k$, and the Jacobians from μ to σ and from μ to γ, we can deduce the derivatives $\partial\sigma/\partial X_k$ and $\partial\gamma/\partial X_k$, respectively.

But, as we consider ratios involving changes in μ, σ and α, we must remember that the first two moments have dimensions but that the third one does not : whereas $\mu = E(y)$ has the same units as $\sigma = \left\{E\left[(y - E(y))\right]^2\right\}^{1/2}$, $\alpha = E\left[(y - E(y))\right]^3/\sigma^3$ has no dimension. Although this heterogeneity of dimensions severely limits our intuitive understanding of ratios computed between the first two and the third moment—they are therefore not reported on in tables—, the signs of those trade-offs remain interpretable.

The interpretation of signs. As in any ratio, the sign of the marginal rate of substitution depends on the sign of the elements, in this case partial derivatives : it will be positive if the derivatives of the two moments have the same sign and negative if they have opposite signs. Table 3 therefore presents expectations concerning the signs of the marginal rates of substitution among the first three moments.

If accidents are objects of interest, and conceived as a « bad », one would expect the sequence of signs to be reversed, but ***the ratios or marginal rates of substitution between any pair of moments to be unaffected in sign***. This is exactly what is indicated in Table 3, where a reference pattern [A] is defined for a risk-averse individual, with a justification for each sign provided both for the case of a return from an hypothetical financial asset (a « good ») and for the case of a road accident (a « bad »). The psychological key to the understanding of this pattern for accidents is to note that, in contrast with the case of the financial return from an asset, a less certain (higher σ) accident is preferred to a more certain accident (lower σ) and that downward risk (asymmetry to the left, i.e. a negative α) is preferred to upward risk (asymmetry to the right, i.e. a positive α). But this *mutatis mutandis* converse preference direction has no impact on the signs of the marginal rates of substitution among moments. Pattern [B] defines a pattern for a risk-lover. Poisson trade-offs of 1 between the first two moments and trade-offs of 0 associated with straight line horizontal indifference curves in the two-moment risk neutral formulation (TOBIN, 1965) are special cases.

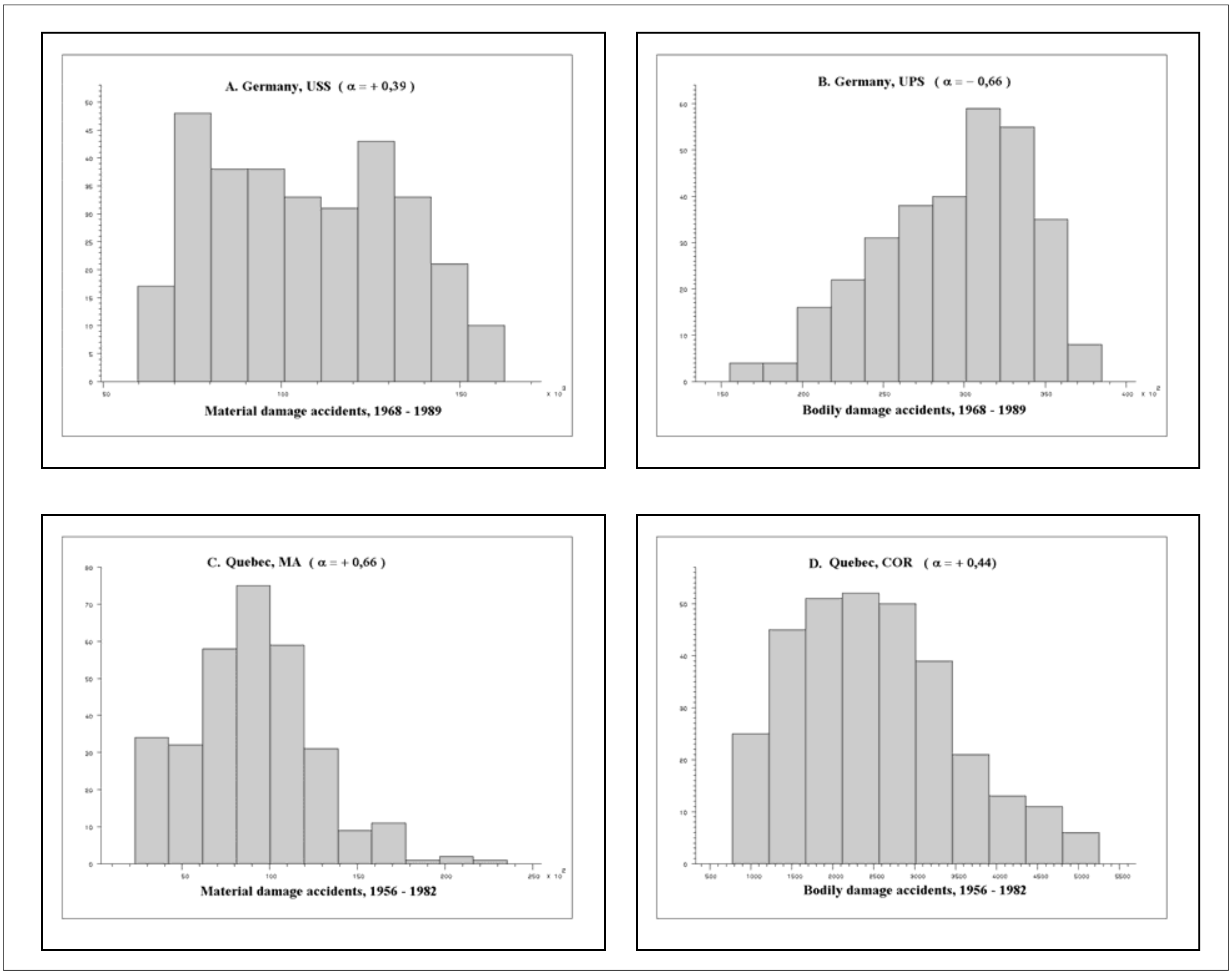
Table 3: Expectations of signs of marginal rates of substitution among moments

<table>
<tr><th colspan="9">Two patterns of marginal rates of substitution ∂ (mom. i)/ ∂ (mom. j)</th></tr>
<tr><td rowspan="2">i\j</td><td colspan="3">[A]. Riscophobe</td><td></td><td colspan="3">[B]. Riscophile</td><td></td></tr>
<tr><td>μ</td><td>σ</td><td>α</td><td></td><td>μ</td><td>σ</td><td>α</td><td></td></tr>
<tr><td>μ</td><td>1</td><td>+</td><td>–</td><td></td><td>1</td><td>–</td><td>+</td><td>Assumed MRS</td></tr>
<tr><td>σ</td><td></td><td>1</td><td>–</td><td></td><td></td><td>1</td><td>–</td><td>Derived MRS</td></tr>
<tr><td>α</td><td></td><td></td><td>1</td><td></td><td></td><td></td><td>1</td><td></td></tr>
<tr><td colspan="9">The [A] pattern of risk aversion for a financial (FIN) asset or a road accident (ACC) means that :</td></tr>
<tr><td>$\partial\mu(y)/\partial\sigma(y) \rangle 0$</td><td colspan="8">(FIN) : greater uncertainty σ is traded against higher return μ ;
(ACC) : more uncertainty σ is traded against higher expected probability μ.</td></tr>
<tr><td>$\partial\mu(y)/\partial\alpha(y) \langle 0$</td><td colspan="8">(FIN) : increased upside risk (decreased downside risk) α is accepted against lower expected return μ ; (ACC) : higher upside accident risk α (decreased downside risk) is accepted against lower expected accident probability μ.</td></tr>
<tr><td>$\partial\sigma(y)/\partial\alpha(y) \langle 0$</td><td colspan="8">(FIN) : increased upside risk (decreased downside risk) α is accepted against lower uncertainty of return σ ; (ACC) : higher upside accident risk (decreased downside risk) is accepted against lower uncertainty (higher certainty) σ of the accident probability. This result follows from the first two.</td></tr>
<tr><td colspan="9">These defined patterns are feasible (Table 6 in LIEM et al. 1999). Riscophilia and riscophobia are defined by assuming particular signs for the marginal rates of substitution (MRS) between the first and other two moments. The MRS between the second and third moments is derived from these, whence its negative sign in both cases.</td></tr>
</table>

4.3 Marginal rates of substitution with comparable accident data

Comparable data but contrasting asymmetries. Germany and Quebec have almost identical definitions of material damage accidents (variable USS for Germany and variable MA for Quebec) and of bodily damage accidents (variable UPS for Germany and COR for Quebec), covering both injury and fatal accidents. There are some minor differences in the definition of « material damage accidents » between these samples, because in Quebec the introduction of a self-reporting mechanism (during the last 3,5 years of the sample) for material damage accidents reduced the number of these accidents reported to the police, the common source of the accident data for both regions : although considered in the model, this may slightly influence both the measured moments and the estimated marginal trade-offs. The frequency distributions are shown in Figure 17, where the observed third moment asymmetry coefficients (other moment measurements are found in Table 4) are shown in the subtitles.

<u>Figure 17 :</u> Accident frequency distributions in Germany and Quebec



It is striking that the observed third moment is strongly negative in Germany for bodily damage accidents (UPS) and positive otherwise, both in Germany (USS) and Quebec (MA, COR). This is not surprising in the sense that, with unregulated speeds, one expects a strong tail to the left (for UPS, $\alpha = -0{,}66$) as drivers aim for a sharply dropping fatal accident probability at high speeds. In speed-regulated environments, where drivers are « forced to prudence » tails to the right are expected, for both material and bodily damage accidents, to the extent that some individuals will not respect the law but that the overwhelming majority will reduce speed. Note also that, in Germany, the aymmetry to the right of the frequency of material damage accidents is tampered by a second peak that may also be related to speed limits : it is as if one observed a mixed distribution consisting in one underlying distribution, asymmetric to the right, dominating another weaker distribution, asymmetric to the left.

Own and cross trade-offs. Table 4 presents the trade-offs within each accident category, as well as the cross category trade-offs, for both Germany and Quebec. Because the lower triangular parts of the matrices present the inverse of the upper triangular part, we do not show all possible rates of substitution.

Table 4: Marginal rates of substitution among moments with comparable data

∂ (mom. i)/ ∂ (mom. j)		**Material damage accidents**			**Bodily damage accidents**		
1. Results Germany		USS			UPS		
SNUS-2.5	**i\j**	μ	σ	α	μ	σ	α
USS	μ	+ 1	+ 23	– ...	– 7,46	+ 124	– ...
	σ		+ 1	– ...	– 0,46	+ 7	– ...
	α			+ 1	+ ...	– ...	+ ...
UPS	μ				+ 1	– 16	+ ...
	σ					+ 1	– ...
	α						+ 1
Sample moment value		103 617	24 149	0,388	29 717	4 724	– 0,661
Fitted value at the means		103 453	5 844	0,127	29 710	1 442	– 0,185
Mean of fitted values		103 616	23 406	0,362	29 706	4 528	– 0,757
2 . Results Quebec		MA			COR		
DRAG-1	**i\j**	μ	σ	α	μ	σ	α
MA	μ	+ 1	+ 15	– ...	+ 6,18	+ 112	– ...
	σ		+ 1	– ...	+ 0,38	+ 7	– ...
	α			+ 1	– ...	– ...	+ ...
COR	μ				+ 1	+ 18	– ...
	σ					+ 1	– ...
	α						+ 1
Sample moment value		9 121	3 478	0,656	2 552	973	0,443
Fitted value at the means		8 998	695	0,186	2 504	178	0,164
Mean of fitted values		9 220	3 374	0,490	2 551	946	0,366

Model fit. The first thing to note in Table 4 is that the first moment is better modeled that the second or third moments (positive or negative), as a comparison between observed and fitted moment values, evaluated either at the sample means of the variables or by the mean of the moment values fitted for individual observations, shows. From our earlier remarks emphasizing the « first moment minded » focus of modeling practice, this is hardly a surprise.

Similar rates of substitution among moments. A second thing to notice in Table 4 is the amazing closeness of the estimated trade-offs both between the first two moments of a given accident category and across accident categories, abstracting for signs found in the case of bodily injury accidents (UPS) in Germany. For instance, in both Germany and Quebec, drivers behave as if they were willing to increase the probability of material damage accidents by about 20 units (15 in DRAG-1, about 21 in DRAG-2 (see GAUDRY, 1998) and 23 in SNUS-2) in order to gain an increase in the uncertainty (a decrease in the certainty) of these material accidents of 1 unit (of standard error). All of these rates are very far from unity, the value assumed to hold in Poisson models.

And they will accept about 115-124 more material damage accidents to obtain an increase in the uncertainty (a decrease in the certainty) of bodily damage accidents of 1 unit (of standard error). It is not a surprise that bodily damage accidents are « worth » more than material damage accidents.

The signs of rates of substitution. The third thing to notice is that all accident types in Germany and Quebec share the same sign pattern of substitution among moments, as indicated in the shaded areas of Part 1 and Part 2 of the table, except for bodily damage accidents (UPS) in Germany. To clarify the meaning of these signs, we use expectations defined in Table 3. Interestingly enough, the own-moment pattern of bodily damage accidents for Germany (UPS *vs* UPS in Part 1) exhibits ***riscophilia***, or type [B], and all 3 other patterns exhibit riscophobia, or type [A]. This means that speed limit regulations somehow force drivers to be riscophobes, at least for the component of their behaviour that is the object of police enforcement (aimed at the first moment, but affecting the third): forced into right-tail skewness—to a strong reduction in α (the values are 0,388 for Germany and, respectively 0,656 and 0,443 for Quebec) and in μ—, they compensate in part for this utility loss by increasing σ.

Elasticities of substitution. Our interpretation is therefore that drivers are riscophiles and that speed limits constrain them by acting principally on the first and third moments of the accident probability. If that is true, one would expect the presence of pent-up tension as drivers, forced into a corner solution, are « kept honest », at least in a first and third moment sense, by the law. As this is a constrained equilibrium, one would expect drivers so restrained to be quite sensitive and ready to re-establish their desired risk certainty equivalent utility. Some evidence to that effect is found in the analysis of $\eta(\text{mom. } i/\text{mom. } j)$, the own elasticities of substitution found in Table 5.

Elasticities measure the sensitivity of the rates of substitution to changes in conditions. We note (in the shaded area) that, in the case of the variable most affected by free speeds (UPS in Germany), the elasticities are indeed much smaller than in the 3 other cases (USS in Germany as well as MA and COR in Quebec), especially for rates of substitution involving the third moment.

<u>Table 5:</u> Own elasticities of substitution among moments with comparable data

η [(mom. i)/ (mom. j)]		**Material damage accidents**				**Bodily damage accidents**		
Germany SNUS-2.5		USS				UPS		
	i\j	μ	σ	α		μ	σ	α (*)
	μ	+ 1,00	+ 1,30	– 3,94		+ 1,00	– 0,81	– 0,47
USS	σ		+ 1,00	– 2,99	UPS		+1,00	+ 0,59
	α			+ 1,00				+ 1,00
Quebec DRAG-1		MA				COR		
	μ	+ 1,00	+ 1,23	– 5,13		+ 1,00	+ 1,29	– 4,23
MA	σ		+ 1,00	– 4,16	COR		+ 1,00	– 3,27
	α			+ 1,00				+ 1,00

(*) Sign inversions found by comparing with Table 4, Part 1, are due to the negative α.

4.4 Marginal rates of substitution with disaggregated accident data

Disaggregation into different categories. The closeness of results obtained for Germany and Quebec is made possible by the existence of comparable data. However, in each case it is possible, as in Table 6, to disaggregate one of the series, but not the corresponding one.

The German series on material damage accidents USS can be split between light and severe damage (ULSS and USSS) events, but this is not possible for the corresponding Quebec series MA. In Quebec, the series on bodily damage acidents COR can be split between injury and fatal (NM and MO) events, but this is not possible for the corresponding German series UPS. One would expect the disaggregated series to yield the same sign patterns as those obtained with their totals, but very different marginal rates of substitution. This is verified in Table 6.

<u>Table 6:</u> Marginal rates of substitution among moments with disaggregated data

∂ (m. i)/ ∂ (m. j)		**Material damage** (USS)						**Bodily damage**		
1. Germany SNUS-2.5	**i\j**	ULSS (light)			USSS (severe)			UPS		
		μ	σ	α	μ	σ	α	μ	σ	α
ULSS	μ	+ 1	+ 18	– ...	+ 1,80	+ 38	– ...	+ 1,04	– 17,5	+ ...
	σ		+ 1	– ...	+ 0,09	+ 2	– ...	+ 0,05	– 0,9	+ ...
	α			+ 1	– ...	– ...	+ ...	– ...	+ ...	– ...
USSS	μ				+ 1	+ 21	– ...	+ 0,58	– 588	+ ...
	σ					+ 1	– ...	+ 0,02	– 27	+ ...
	α						+ 1	– ...	+ ...	– ...
UPS	μ							+ 1	– 16	+ ...
	σ								+ 1	– ...
	α									+ 1
Sample values		79 787	22 389	0,821	23 842	9 026	0,884	29 717	4 724	–0,661
Fitted at means		79 510	4 781	0,158	23 850	1 290	0,138	29 710	1 442	–0,185
Mean of fitted		79 768	21 739	0,815	23 813	8 832	0,876	29 706	4 528	–0,757

∂ (m. i)/ ∂ (m. j)		**Material damage**			**Bodily damage** (COR)					
2. Quebec DRAG-1	**i\j**	MA			NM (injury)			MO (fatal)		
		μ	σ	α	μ	σ	α	μ	σ	α
MA	μ	+ 1	+ 15	– ...	+ 5,87	+ 110	– ...	+73455	+ 7538	– ...
	σ		+ 1	– ...	+ 0,36	+ 6	– ...	+ 4600	+ 472	– ...
	α			+ 1	– ...	– ...	+ ...	– ...	– ...	+ ...
NM	μ				+ 1	+ 18	– ...	+12506	+ 1283	– ...
	σ					+ 1	– ...	+ 666	+ 68	– ...
	α						+ 1	– ...	– ...	+ ...
MO	μ							+ 1	+ 0,10	– ...
	σ								+ 1	– ...
	α									+ 1
Sample values		9 121	3 478	0,656	2 445	939	0,474	107	42	0,237
Fitted at means		8 998	695	0,186	2 375	174	0,158	99	13	0,292
Mean of fitted		9 220	3 374	0,490	2 444	913	0,389	107	39	0,010

Note, for instance that in Quebec the previous marginal rate of substitution between first moments was 6,18 material damages accident per corporal damage accident in Table 4, whereas the component rates in Table 6 are 5,87 material damage accidents per injury accidents and 73 455 material damage accidents per fatal accident. As expected, the « bumpers *vs* limb » rate is much lower than the « bumpers *vs.* life » rate. And the trade-off measured with an aggregate number differs from the trade-off against its components.

In Germany, the marginal rate of substitution between first moments, previously -7,46 material damage accidents per bodily injury is now, in terms of light material damage accidents, 1,80 per severe damage accident and 1,04 per bodily injury accident : having a « bumper *vs* bumper » rate higher than the « bumper vs limb » rate naturally depends on how expensive the marginal « expensive bumpers » are and on how trivial the marginal « small injuries » that may dominate the bodily damage series are. Although the trade-offs measured with aggregates were almost identical with those of Quebec, trade-offs among their components are again different. The absence of comparable disaggregated series unfortunately prevents us from effecting a complete comparison between the results for Germany and Quebec.

Multiple moment choices and homeostasis. However, it is quite clear overall that drivers do make multimoment choices, so that any attempt to determine whether they maintain their utility by adjusting only one moment, such as the first, cannot be a meaningful way of testing a « constant risk » or « constant expected utility » assumption : such an assumption should be formulated as a « constant certainty equivalence of risk » to be amenable to tests, and the tests at least apply to marginal rates of substitution among the moments of an accident category and across categories.

5. Policy implications

5.1 Higher prices save energy and lifes

Our results show that road demand is rather inelastic with respect to fuel prices – which limits the potentials of pure pricing strategies if a reduction of mobility is politically wanted. Increased prices of mobility also reduce the number of accidents and their severity. This effect can be partly offset by activity variables that have a positive impact on road demand and on material damage. Within the category of activities, compensatory effects can be found especially with respect to bodily damage and mortality.

5.2 Risk substitution in terms of first moments

Considering the results obtained in terms of first moments of the various frequency and severity categories, we find strong evidence of risk substitution in the case of belt usage. The alcohol limit imposed in August of 1973 has considerably reduced the number of accidents of all categories. Differentiated weather conditions also lead to a complex pattern of risk compensation that may also be explained by changes in speed and congestion. Speed limits have rather complicated impacts on accidents –contrary to much colloquial and political wisdom.

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Appendix 3.1. Definition of dependent variables in model SNUS-2.5

Tablex Column	**Code name**	**Definition of dependent variable**
Demand		
1	KMBL	Kilometrage by gasoline vehicles
2	KMDL	Kilometrage by diesel vehicles
Accident frequency		
3	ULSS	Light material damage accidents
4	USSS	Severe material damage accidents
5	USS	Total material damage accidents (3+4)
6	UPS	Bodily damage accidents
7	UG	Total accidents (5+6)
Accident severity		
8	MBL	Morbidity light: lightly injured per bodily damage accident
9	MBS	Morbidity light: severely injured per bodily damage accident
10	MB	Morbidity: total injured per bodily damage accident (8+9)
11	MO	Mortality: killed per bodily damage accident

Appendix 3.1. Estimation results of SNUS-2.5

I. ELASTICITY E(y) (EP) (COND. T-STATISTIC)		TYPE =	LEVEL-1	LEVEL-1	LEVEL-1	LEVEL-1	LEVEL-1	LEVEL-1	LEVEL-1	LEVEL-1	LEVEL-1	LEVEL-1	LEVEL-1
		VARIANT =	BV	DV	ULSS	USSS	USS	UPS	UG	MBL	MBS	MB	MO
		VERSION =	9	5	2	2	2	7	3	4	4	4	4
		DEP.VAR. =	KMBL	KMDL	ULSS	USSS	USS	UPS	UG	MBL	MBS	MB	MO
EXPOSURE													
TOTAL VEHICLE KILOMETERS	KML				.237 (2.28) LAM 1	.314 (2.92) LAM 1	.082 (.72) LAM 1	.197 (2.11) LAM 2	.458 (4.98) LAM 1				
GASOLINE CAR USE INDEX (MIX)	GCUI									.010 (.21) LAM 2	.137 (2.17) LAM 2	-.018 (-.56) LAM 2	.557 (2.84) LAM 1
PRICES													
REAL PRICE OF DIESEL	RBPD			-.255 (-1.96) LAM 1									
REAL PRICE OF GASOLINE AND DIESEL	RPNSD				-.122 (-1.37) LAM 1	.023 (.23) LAM 1	-.145 (-1.70) LAM 1	-.047 (-.70) LAM 2	-.004 (-.06) LAM 1	-.059 (-3.18) LAM 2	-.007 (-.24) LAM 2	-.036 (-4.11) LAM 2	-.095 (-1.38) LAM 1
REAL PRICE OF GASOLINE (N+S) CORRECTED	RBPNSC		-.183 (-4.64) LAM 1										
MOTOR VEHICLE - QUANTITY													
CARS (USING GASOLINE) PER EMPLOYEE	PKWBPE		-.492 (-1.54) LAM 2										
SQUARE OF CARS (USING GASOLINE) PER EMPLOYEE	PKWBPE2		.044 (2.11) LAM 2										
CARS (USING DIESEL) PER EMPLOYEE	PKWDPE			.875 (7.79)									
SQUARE OF CARS (USING DIESEL) PER EMPLOYEE	PKWDPE2			-.340 (-5.56)									
MOTOR VEHICLE - CHARACTERISTICS													
BELT USAGE IN %, CORRECTED	GAQC				.265 (5.52) LAM 1	.017 (.31) LAM 1	.099 (2.42) LAM 1	-.114 (-3.04) LAM 2	.187 (5.23) LAM 1	-.002 (-.17) LAM 2	-.051 (-2.25) LAM 2	-.040 (-7.25) LAM 2	-.114 (-2.98) LAM 1
LAWS REGULATION POLICE													
ALCOHOL LIMIT 1.AUGUST 1973	P08		-.026 (-1.61)	-.020 (-.68)	-.085 (-2.38)	-.098 (-2.00)	-.092 (-3.05)	-.087 (-2.68)	-.073 (-2.48)	-.015 (-1.69)	-.015 (-1.01)	-.015 (-3.98)	-.009 (-.37)

Appendix 3.1. Estimation results of SNUS-2.5 (continued)

I. ELASTICITY E(y) (EP) (COND. T-STATISTIC)		TYPE =	LEVEL-1	LEVEL-1	LEVEL-1	LEVEL-1	LEVEL-1	LEVEL-1	LEVEL-1	LEVEL-1	LEVEL-1	LEVEL-1	LEVEL-1
		VARIANT =	BV	DV	ULSS	USSS	USS	UPS	UG	MBL	MBS	MB	MO
		VERSION =	9	5	2	2	2	7	3	4	4	4	4
		DEP.VAR. =	KMBL	KMDL	ULSS	USSS	USS	UPS	UG	MBL	MBS	MB	MO
NETWORK - TIME SERVICE LEVELS													
100 KM/H SPEED LIMIT	HHG		.003	-.013	-.022	-.022	-.018	-.031	-.034	-.007	-.020	-.005	-.023
1972+ SINCE	===		(.09)	(-.35)	(-.47)	(-.41)	(-.47)	(-.71)	(-.88)	(-.67)	(-1.25)	(-1.33)	(-.65)
1974 ON STATE ROADS													
LOWER SPEED	NHG7374		-.040	-.022	-.059	-.154	-.069	-.085	-.107	-.015	-.024	-.008	-.067
HIGHWAYS +	=======		(-1.26)	(-.41)	(-1.04)	(-2.41)	(-1.34)	(-1.25)	(-2.27)	(-.94)	(-.97)	(-1.47)	(-1.57)
STATE ROADS 10/73-4/74													
NETWORK - INFRASTRUCTURE WEATHER													
TEMPERATURE IN	TFF		.011	.046	-.081	-.052	-.075	.046	-.044	-.006	.009	-.005	.051
FRANKFURT (FAHRENHEIT)			(.85)	(1.42)	(-2.91)	(-2.01)	(-3.03)	(2.34)	(-1.70)	(-1.13)	(1.15)	(-1.72)	(2.50)
			LAM 1	LAM 1	LAM 1	LAM 1	LAM 1	LAM 2	LAM 1	LAM 2	LAM 2	LAM 2	LAM 1
HOURS OF	SSDF		.017	.006	-.020	-.051	-.021	.045	-.021	-.003	.002	-.004	.001
SUNSHINE IN FRANKFURT			(2.67)	(.36)	(-1.21)	(-3.72)	(-1.11)	(3.09)	(-1.52)	(-.71)	(.39)	(-1.72)	(.05)
			LAM 1	LAM 1	LAM 1	LAM 1	LAM 1	LAM 2	LAM 1	LAM 2	LAM 2	LAM 2	LAM 1
MM OF RAIN	NIF		.002	-.004	.000	.009	.001	-.000	.001	.001	-.001	-.001	.019
RAINYDAYS IN FRANKFURT			(.38)	(-.30)	(.03)	(.87)	(.08)	(-.06)	(.07)	(.33)	(-.29)	(-.57)	(1.93)
			LAM 1	LAM 1	LAM 1	LAM 1	LAM 1	LAM 2	LAM 1	LAM 2	LAM 2	LAM 2	LAM 1
RAINY DAYS	RF		-.003	-.012	.037	.046	.039	.019	.038	.005	-.005	.001	-.018
IN FRANKFURT			(-.65)	(-1.27)	(3.77)	(5.64)	(4.28)	(2.40)	(4.66)	(2.16)	(-2.10)	(1.02)	(-1.98)
			LAM 1	LAM 1	LAM 1	LAM 1	LAM 1	LAM 2	LAM 1	LAM 2	LAM 2	LAM 2	LAM 1
CONSUMERS - GENERAL CHARACT.													
PROVISIONAL DRIVING	FSP				.042	-.041	-.014	-.059	.007	.013	-.002	.008	-.042
LICENSE FOR NEW	===				(1.18)	(-.63)	(-.35)	(-2.25)	(.25)	(1.67)	(-.16)	(2.17)	(-1.43)
DRIVERS 1.1.1987													
CONSUMERS - EBRIETY OR VIGILANCE													
REAL RETAIL SALES IN	REUAERW				.197	.000	.175	.066	.097	.071	-.023	-.006	.257
DRUGSTORES PER ADULT					(1.47)	(.00)	(1.45)	(.66)	(.89)	(2.98)	(-.88)	(-.32)	(3.23)
					LAM 1	LAM 1	LAM 1	LAM 2	LAM 1	LAM 2	LAM 2	LAM 2	LAM 1
BEER PRODUCTION	BIERPE		.204										
(LITERS) PER EMPLOYEE			(3.68)										
			LAM 1										
BEER PRODUCTION PER	BIERPEKMB				-.306	-.305	-.263	.103	-.187	-.069	.002	-.014	-.010
EMPLOYEE AND					(-2.54)	(-3.12)	(-2.49)	(1.34)	(-2.00)	(-2.95)	(.09)	(-1.12)	(-.11)
GASOLINE KILOMETER					LAM 1	LAM 1	LAM 1	LAM 2	LAM 1	LAM 2	LAM 2	LAM 2	LAM 1

Appendix 3.1. Estimation results of SNUS-2.5 (continued)

I. ELASTICITY E(y) (EP) (COND. T-STATISTIC)		TYPE =	LEVEL-1	LEVEL-1	LEVEL-1	LEVEL-1	LEVEL-1	LEVEL-1	LEVEL-1	LEVEL-1	LEVEL-1	LEVEL-1	LEVEL-1
		VARIANT =	BV	DV	ULSS	USSS	USS	UPS	UG	MBL	MBS	MB	MO
		VERSION =	9	5	2	2	2	7	3	4	4	4	4
		DEP.VAR. =	KMBL	KMDL	ULSS	USSS	USS	UPS	UG	MBL	MBS	MB	MO
ACTIVITIES - FINAL AND INTERMEDIATE													
EMPLOYEE PRESENCE	EPIFT		.032										
INDEX			(1.58)										
(NON FREE DAYS)			LAM 1										
EMPLOYEE PRESENCE	EPIFTKMB				.037	.028	.024	-.037	.017	-.048	-.007	-.014	-.078
INDEX PER					(1.45)	(1.37)	(.75)	(-1.02)	(.48)	(-2.99)	(-1.36)	(-3.63)	(-2.15)
GASOLINE KILOMETER					LAM 1	LAM 1	LAM 1	LAM 2	LAM 1	LAM 2	LAM 2	LAM 2	LAM 1
LONG DIST. TRUCK	FVLKWPE		.192	.458									
TRANSP.			(4.08)	(5.18)									
(TONS) PER EMPLOYEE			LAM 1	LAM 1									
FOOD + CLOTHING	REUNBPE		.214	.388									
SALES PER EMPLOYEE			(6.15)	(5.93)									
			LAM 1	LAM 1									
FOOD + CLOTHING	REUNBPEKMB				.406	.369	.407	.107	.356	-.000	.015	.016	-.111
SALES PER E AND KMB					(5.70)	(5.69)	(5.70)	(2.47)	(6.37)	(-.01)	(2.08)	(1.94)	(-1.68)
					LAM 1	LAM 1	LAM 1	LAM 2	LAM 1	LAM 2	LAM 2	LAM 2	LAM 1
TOTAL OVERNIGHT	UENGPE		.047	.103									
STAYS PER EMPLOYEE			(3.77)	(2.81)									
			LAM 1	LAM 1									
OVERNIGHT STAYS PER	UENGPEKMB				.079	.078	.072	-.078	.088	.019	.013	.037	-.054
EMPLOYEE AND					(1.71)	(2.51)	(1.62)	(-2.27)	(2.85)	(2.20)	(3.25)	(5.59)	(-.91)
GASOLINE KILOMETER					LAM 1	LAM 1	LAM 1	LAM 2	LAM 1	LAM 2	LAM 2	LAM 2	LAM 1
FREE DAYS IN CONTEXT	FRTMFG		.011	-.010	-.007	-.008	-.010	-.042	-.016	-.007	.004	.001	-.014
OF HOLIDAYS, WEIGHTED			(2.01)	(-1.60)	(-1.06)	(-1.60)	(-1.27)	(-3.38)	(-1.69)	(-1.40)	(2.43)	(.70)	(-1.26)
			LAM 1	LAM 1	LAM 1	LAM 1	LAM 1	LAM 2	LAM 1	LAM 2	LAM 2	LAM 2	LAM 1
ET CETERA - ADMINISTRATIVE													
SEVERE MATERIAL	SSSKIC				.314	-.735							
DAMAGE					(11.20)	(-10.99)							
CLASSIFICATION VALUE					LAM 1	LAM 1							
ET CETERA - AGGREGATION													
WORKDAYS	AT				.354	.319	.421	.320	.259		-.022	-.027	-.134
					(2.24)	(2.69)	(3.09)	(3.24)	(2.21)		(-.73)	(-1.44)	(-1.19)
					LAM 1	LAM 1	LAM 1	LAM 2	LAM 1		LAM 2	LAM 2	LAM 1
SATURDAYS	ST		-.082	-.105	-.014	.031	-.004	.097	.032	-.013	.029	.009	.037
			(-4.05)	(-2.54)	(-.27)	(.75)	(-.08)	(3.02)	(.81)	(-1.52)	(2.81)	(1.59)	(1.00)
			LAM 1	LAM 1	LAM 1	LAM 1	LAM 1	LAM 2	LAM 1	LAM 2	LAM 2	LAM 2	LAM 1
SUNDAYS AND HOLIDAYS	SF		-.000	-.056	.116	.101	.108	.129	.101	-.004	.024	.007	.041
			(-.01)	(-1.85)	(2.34)	(2.69)	(2.45)	(3.84)	(2.66)	(-.66)	(2.47)	(1.06)	(1.01)
			LAM 1	LAM 1	LAM 1	LAM 1	LAM 1	LAM 2	LAM 1	LAM 2	LAM 2	LAM 2	LAM 1

Appendix 3.1. Estimation results of SNUS-2.5 (continued)

I. ELASTICITY E(y) (EP) (COND. T-STATISTIC)		BV	DV	ULSS	USSS	USS	UPS	UG	MBL	MBS	MB	MO
TYPE =		LEVEL-1	LEVEL-1	LEVEL-1	LEVEL-1	LEVEL-1	LEVEL-1	LEVEL-1	LEVEL-1	LEVEL-1	LEVEL-1	LEVEL-1
VARIANT =		BV	DV	ULSS	USSS	USS	UPS	UG	MBL	MBS	MB	MO
VERSION =		9	5	2	2	2	7	3	4	4	4	4
DEP.VAR. =		KMBL	KMDL	ULSS	USSS	USS	UPS	UG	MBL	MBS	MB	MO
ASSOCIATED DUMMIES GROUP												
FREE DAYS IN CONTEXT OF HOLIDAYS, WEIGHTED	FRTMFG ======	-.011 (-.93)	.003 (.10)	-.033 (-1.40)	-.018 (-1.03)	-.030 (-1.45)	-.026 (-1.55)	-.011 (-.62)	.002 (.46)	.003 (.42)	-.000 (-.08)	.013 (.65)
REGRESSION CONSTANT	CONSTANT	- (2.77)	- (23.72)	- (2.87)	- (4.95)	- (-.04)	- (2.49)	- (1.91)	- (-2.35)	- (-2.46)	- (9.78)	- (-7.61)
HETEROSKEDASTICITY STRUCTURE												
DELTA COEFFICIENTS												
EMPLOYEES PER GASOLINE KILOMETER	EKMB								.172 (2.20) LAM 2			

II. PARAMETERS (COND. T-STATISTIC)		BV	DV	ULSS	USSS	USS	UPS	UG	MBL	MBS	MB	MO
TYPE =		LEVEL-1	LEVEL-1	LEVEL-1	LEVEL-1	LEVEL-1	LEVEL-1	LEVEL-1	LEVEL-1	LEVEL-1	LEVEL-1	LEVEL-1
VARIANT =		BV	DV	ULSS	USSS	USS	UPS	UG	MBL	MBS	MB	MO
VERSION =		9	5	2	2	2	7	3	4	4	4	4
DEP.VAR. =		KMBL	KMDL	ULSS	USSS	USS	UPS	UG	MBL	MBS	MB	MO
HETEROSKEDASTICITY STRUCTURE												
BOX-COX TRANSFORMATIONS: UNCOND: [T-STATISTIC=0] / [T-STATISTIC=1]												
LAMBDA(Z) - GROUP 2	LAM 2								.034 [.10] [-2.69]			
BOX-COX TRANSFORMATIONS: UNCOND: [T-STATISTIC=0] / [T-STATISTIC=1]												
LAMBDA(Y) - GROUP 1	LAM 1	.309 [2.06] [-4.60]	.091 [.90] [-8.95]	.081 [.80] [-9.02]	.125 [1.67] [-11.67]	.233 [2.45] [-8.07]	2.214 [7.35] [4.03]	.388 [2.75] [-4.35]	-3.198 [-1.63] [-2.14]	.973 [2.04] [-.06]	-2.722 [-1.85] [-2.53]	.528 [3.17] [-2.83]
LAMBDA(X) - GROUP 1	LAM 1	.309 [2.06] [-4.60]	.091 [.90] [-8.95]	.081 [.80] [-9.02]	.125 [1.67] [-11.67]	.233 [2.45] [-8.07]		.388 [2.75] [-4.35]				.528 [3.17] [-2.83]
LAMBDA(X) - GROUP 2	LAM 2	-3.296 [-2.48] [-3.24]					1.200 [5.71] [.95]		.947 [4.77] [-.27]	2.183 [3.71] [2.01]	.276 [1.35] [-3.56]	

Appendix 3.1. Estimation results of SNUS-2.5 (end)

II. PARAMETERS (COND. T-STATISTIC)		TYPE =	LEVEL-1	LEVEL-1	LEVEL-1	LEVEL-1	LEVEL-1	LEVEL-1	LEVEL-1	LEVEL-1	LEVEL-1	LEVEL-1	LEVEL-1
		VARIANT =	BV	DV	ULSS	USSS	USS	UPS	UG	MBL	MBS	MB	MO
		VERSION =	9	5	2	2	2	7	3	4	4	4	4
		DEP.VAR. =	KMBL	KMDL	ULSS	USSS	USS	UPS	UG	MBL	MBS	MB	MO
AUTOCORRELATION													
ORDER 1	RHO 1		.229	.350	.339	.494	.397	.501	.331	.471	.394	.377	.290
			(3.29)	(5.34)	(5.56)	(6.08)	(6.56)	(9.42)	(5.39)	(8.80)	(5.83)	(5.76)	(4.44)
ORDER 2	RHO 2					.093							
						(1.38)							
ORDER 3	RHO 3										.214		
											(3.71)		
ORDER 4	RHO 4		.215		.118	.175	.149		.187		.124	-.203	
			(3.48)		(1.57)	(2.69)	(2.60)		(2.41)		(1.49)	(-5.05)	
ORDER 5	RHO 5		.252					-.105					
			(3.33)					(-4.13)					
ORDER 7	RHO 7		.232										
			(3.31)										
ORDER 8	RHO 8									.077	.207		
										(1.68)	(2.96)		
ORDER 10	RHO 10		-.148					.094	-.077				
			(-2.46)					(1.67)	(-.96)				
ORDER 11	RHO 11				.132	.129	.199	.211		.196		.203	.359
					(2.16)	(1.81)	(3.08)	(2.63)		(3.17)		(3.60)	(7.37)
ORDER 12	RHO 12		.197	.254	.185	.088	.258	.210	.293	.094		.194	.246
			(2.47)	(3.96)	(3.24)	(1.23)	(4.26)	(2.81)	(4.51)	(1.30)		(2.87)	(3.30)
ORDER 13	RHO 13		-.108								.106	.098	.129
			(-1.69)								(1.71)	(1.54)	(2.03)
ORDER 20	RHO 20		-.091										
			(-1.28)										
ORDER 24	RHO 24									.173			
										(2.91)			
ORDER 36	RHO 36		.195										
			(3.77)										

III.GENERAL STATISTICS	TYPE =	LEVEL-1	LEVEL-1	LEVEL-1	LEVEL-1	LEVEL-1	LEVEL-1	LEVEL-1	LEVEL-1	LEVEL-1	LEVEL-1	LEVEL-1
	VARIANT =	BV	DV	ULSS	USSS	USS	UPS	UG	MBL	MBS	MB	MO
	VERSION =	9	5	2	2	2	7	3	4	4	4	4
	DEP.VAR. =	KMBL	KMDL	ULSS	USSS	USS	UPS	UG	MBL	MBS	MB	MO
LOG-LIKELIHOOD		-3896.33	-4256.34	-2484.92	-2147.71	-2538.26	-2193.89	-2568.96	737.680	901.054	789.753	1219.469
PSEUDO-R2 : - (E)		.988	.965	.951	.978	.940	.888	.928	.822	.970	.938	.961
- (L)		.987	.972	.957	.982	.943	.904	.928	.832	.970	.938	.962
SAMPLE : - NUMBER OF OBSERVATIONS		228	252	252	252	252	252	252	240	251	251	251
- FIRST OBSERVATION		37	13	13	13	13	13	13	25	14	14	14
- LAST OBSERVATION		264	264	264	264	264	264	264	264	264	264	264
NUMBER OF ESTIMATED PARAMETERS :												
- FIXED PART :												
. BETAS		20	18	23	23	22	22	22	21	22	22	22
. BOX-COX		2	1	1	1	1	2	1	2	2	2	1
. ASSOCIATED DUMMIES		1	1	1	1	1	1	1	1	1	1	1
- AUTOCORRELATION		9	2	4	5	4	5	4	5	5	5	4
- HETEROSKEDASTICITY :												
. DELTAS		0	0	0	0	0	0	0	1	0	0	0
. BOX-COX		0	0	0	0	0	0	0	1	0	0	0
. ASSOCIATED DUMMIES		0	0	0	0	0	0	0	0	0	0	0