Speed and Income

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Abstract
The average speed on Danish motorways has been increasing for a number of years. In this paper we seek to provide at least a partial explanation for this development. First we establish in a micro-economic model how higher income can lead to a higher choice of speed. With increasing income, the value of time increases and the costs of driving faster decrease in importance, both operating costs and potential fines. Second, we utilize a cross-section dataset comprising 60.000 observations of car trips to perform a regression of speed on income, distance traveled and a number of controls. The results indicate a clear relationship between speed and income whereby a 100.000 kroner increase in pretax income, about 35 percent of the average income in the sample, is associated with a speed increase of 2 km/h at longer distances.

Keywords: speed, income

Introduction

The issue of speeds on Danish roads has come into focus with the recent political decision to increase the general speed limit on motorways from 110 km/h to 130 km/h. There has been a prolonged public debate concerning whether speeds will actually increase after such a change and on the likely effect of increased enforcement.

Average speeds have been increasing on Danish motorways for many years and certainly since 1986 when continuous measurement of speeds begun. In the period from 1986 to 1998, the average speed for all vehicles in open country increased from 103 km/h to 114 km/h. The current average speed for passenger cars is 119 km/h, while the speed limit is still 110 km/h (Danmarks TransportForskning, 2002). This development, shown as an index in figure 1, represents somewhat of a puzzle, since there is little apparent relationship with changes in speed limits and enforcement. In 1992 the general speed limit on motorways for passenger cars was increased from 100 to 110 km/h and there was a political decision to increase enforcement, which, however, did not result in more fines being presented. There is actually a general decrease in the number of fines given over the period from 1986 to 1998, as recorded by the police (Dansk Politi, various years).

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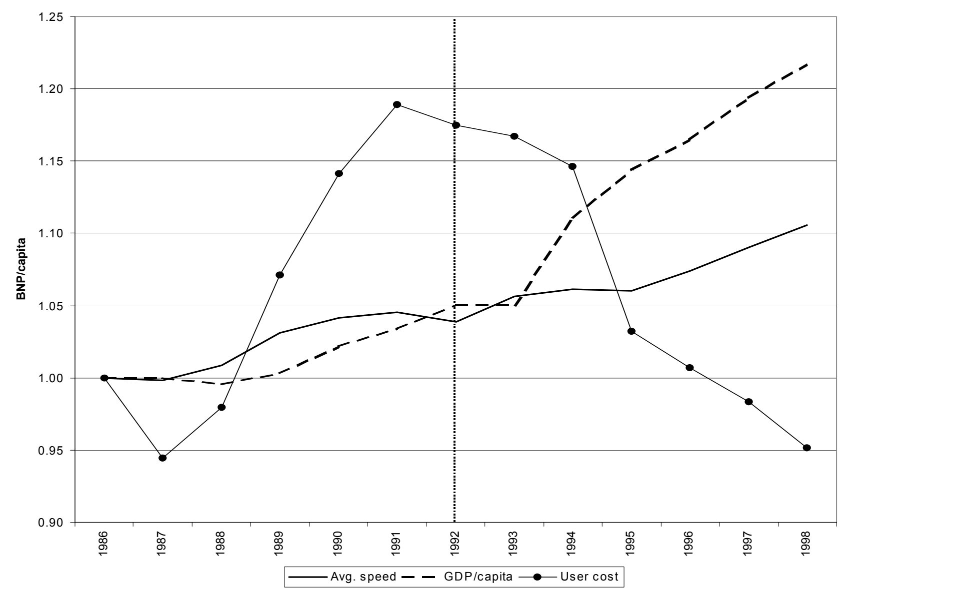

Figure 1. The average speed on Danish motorways, real GDP per capita and user cost of car use

Figure 1 also presents the increase in real GDP per capita over the same period. It is evident that both the average speed and average income have been increasing, but it is not possible on basis of this short time series to draw any firm conclusions regarding the relationship.

Nevertheless, we will advance the view that income growth is a likely driver behind the increase in speed. We assume that car drivers generally want to drive as fast as possible, ceteris paribus. They are, however, constrained by accident risk, fuel costs increasing with speed above a certain level and the risk of receiving a fine. As income grows, fuel costs and fines are less constraining.

There is the further relationship that driving faster can induce discomfort through noise and vibrations. The consumer can compensate by buying a high quality car, which is more comfortable at higher speeds. As income grows, consumers can afford better quality cars. The relationship between income and the quality of the car is very clear and documented, e.g., in Birkeland and Fosgerau (1999).

The price of quality may also have had a separate effect. Figure 1 also shows a real user cost index for car ownership, including costs of vehicles, maintenance, annual tax and fuel (Danmarks Statistik, 2003). Up to 1991 the user cost index increased by 19 percentage points, thereafter followed a long decrease until 1998 by 24 percentage points. It is likely that this development also has had some effect on the observed average speed, but we shall not focus on this issue.

Thus, we expect average speed to increase with average income. In this paper we shall show this in a simple micro-economic model and then validate the relationship using a large cross-sectional dataset.

The previous literature contains little on the relationship between speed and income. There are more studies on the relationship between economic factors and crashes. Recently, Scuffham and Langley (2002) performed a time series analysis of the number of crashes using i.a. real GDP and unemployment as explanatory variables. Both variables are closely related to personal incomes. Their results suggest that increases in income were associated mainly with increases in exposure to a crash, proxied by distance travelled, but they did not detect a significant influence of income on the risk of a crash for a given level of exposure. They note that increasing income may increase the level of vehicle safety and thereby decrease the risk of a crash. On the other hand, drivers may compensate for lower risk by driving faster, with less attention or less concern for safety. They do not consider the direct effect of income on speed.

Hakim and Shefer (1991) review a number of macro models for road accidents. Generally, income influences the demand for travel, which in turn influences the number of accidents. In the long run, income growth could increase the demand for safer cars and the supply of safer roads, leading to a decrease in the fatality rate per km for a given demand for travel. They argue that including both income and the demand for travel as independent variables in the same model will lead to biased estimates due to the double-counting occurring, when income is also a determinant of travel demand.

From the point of view of this paper it is interesting to note a similar problem in some of the papers reviewed by Hakim and Shefer, where both average speed and income (in some form) are used to explain the number of accidents. Zlatoper (1991) also includes both speed and income to explain the number of accidents in a single regression. But average speed must be regarded as an endogenous variable depending on income, as we shall argue in this paper, and thus inclusion of both as independent variables in a single regression is likely to bias results.

Gander (1985) presents a household utility model with highway automobile speed and uncertain enforcement, focusing on the risk attitude of the driver and the effect on optimal speed of such attitude. This model is in many ways similar to the one presented here, except we do not focus on the risk behaviour, which allows for some simplification.

Empirical results on the relationship between speed and income are found in Shinar et al. (2001) who study interview data, including a question on how often respondents drive at or below the speed limit. The results indicate a clear significant relationship between income and whether the respondent stated that he/she observed the speed limit "all the time". Similarly, there were relationships between the probability of observing speed limits and age, sex and education. In comparison to Shinar et al. we study directly the speed rather than an indirect binary variable (observe the speed limit all the time). In addition, we have a much larger sample with almost 60,000 observations. With our data, it is possible to observe how the dependence of speed on income varies with increasing travel distance.

The layout of this paper is as follows. In section 2 we first demonstrate the relationship between speed and income in a simple theoretical model. Then for the empirical analysis in section 3, we utilise a large micro-dataset from the Danish national travel survey. Finally, section 4 contains some concluding remarks.

Theoretical analysis

Consider a consumer with a utility function U(X) depending on consumption X. The utility function is increasing and concave in X, such that the first derivative is positive and the second negative, implying that the consumer is risk-averse. Disregarding leisure, he spends his total time allocation T on work and travel only. With a fixed driving distance normalised to 1 and travel speed S, the time spent travelling is 1/S. Given the wage rate w, the income available for consumption is w(T-1/S). Thus the consumer attaches the value w to each unit of time that can be saved by driving faster. The concept of a value of time is standard in models of travel demand, (e.g. Ortúsar and Willumsen, 1994).

However, the consumer risks receiving a fine: Being caught speeding is a random event described by the random variable C, which is 1 if caught and 0 otherwise. Using the same assumption as Gander (1985), the fine is taken to increase linearly with speed in excess of the speed limit S_0, resulting in the payment $CF(S-S_0)$. This is the structure of fines in Denmark. Like Gander, we assume that $S>S_0$, i.e. the consumer always drives too fast, which is true on average on Danish motorways. Normalising the price of consumption to 1, the consumption is then given as a function of the chosen speed and whether the consumer is caught speeding.

$$X(S,C)=w(T-1/S)-CF(S-S_0)$$

Substitute this into the utility function to achieve V(S,C)=U(X(S,C)). The partial derivative of V with respect to speed is $V_S(S,C)=U_X(X(S,C))(w/S^2-CF)$. We assume that the probability of being caught is constant, $P(C=1)=\pi$. We could alternatively assume that the probability increases with speed. However, this would unnecessarily complicate the analysis and not change the general results.

Then the expected utility given speed is $EV(S,C)=\pi V(S,1)+(1-\pi)V(S,0)$. The consumer maximises this expected utility with respect to speed. We compute the first order condition for maximum as

$$\pi U_X(X(S,1))(w/S^2-F)+(1-\pi)U_X X(S,0)w/S^2=0.$$

Solving this with respect to S results in

$$2\log S=\log(w/\pi F)+\log[\pi U_X(X(S,1))+(1-\pi)U_X(X(S,0))]-\log U_X(X(S,1)).$$

In order to avoid long and tedious derivations, we assume that the fine paid is small relative to consumption, such that $|U_X(X(S,0))-U_X(X(S,1))|< \varepsilon$ for some small ε. Note that this does not imply that $\log U_X(X(S,0))-\log U_X(X(S,1))$ is also small. Using this to approximate we rewrite as

$$\begin{aligned}
&2\log S \approx \log(\frac{w}{\pi F})+\log U_X(X(S,0))-\log U_X(X(S,1)) \\
&\approx \log(\frac{w}{\pi F})+\frac{\partial \log U_X}{\partial X}(X(S,1))(X(S,0)-X(S,1)) \\
&=\log(\frac{w}{\pi F})+\frac{U_{XX}(X(S,1))}{U_X(X(S,1))}F(S-S_0)
\end{aligned}$$

For simplicity we introduce the notation $\gamma = U_{XX}(X(S,1))/U_X(X(S,1))$, and note that $\gamma<0$ since the utility function is increasing and concave. With this notation we have

(1) $$2\log S = \log(w/\pi F) + \gamma F(S - S_0).$$

We are now ready to examine the relationship between income and speed by differentiating this equation with respect to income w.

$$\frac{\partial S}{\partial w} = \frac{S}{2}\frac{\partial 2\log S}{\partial w} = \frac{S}{2}\left(\frac{1}{w} + \gamma F\frac{\partial S}{\partial w}\right) = \frac{1}{w}\frac{S}{2 - \gamma SF} > 0$$

This shows, as expected, that speed increases with income. Similar calculations are easily performed to show that speed decreases when the probability of receiving a fine increases, when the size of the fine increases and when the speed limit increases. Introducing speed dependent fuel consumption complicates the derivations somewhat but the conclusions concerning signs of effects remain the same with the addition that an increased fuel price decreases speed.

We have not yet considered the quality of the car. One option is to introduce a second term in the utility function, $U=(X,G(S,Q))$, describing the driving comfort. This would decrease with speed and increase with the quality of the car, where the quality of the car is bought at a price per quality unit. This would intuitively preserve the conclusions made here, with the additional conclusion that speed would decrease when the price of quality is increased. This result is easy to derive, when the risk of a fine is neglected ($\pi=0$).

Empirical results

For the empirical test of the relationship between speed and income we utilise the Danish National Travel Survey, which is a continuous telephone interview survey of about 15-17,000 respondents annually (Danmarks TransportForskning, 2003). We select 86,491 observations of car driver trips from the period 1996-2001, where both trip ends are outside the relatively congested capital region around Copenhagen. Discarding observations where income is not recorded leaves 76001 observations.

We further discard 15843 observations of trips below 2 kilometres, as the time involved in starting the car and getting onto the larger roads is likely to dominate results. We discard 225 observations of trips above 200 kilometres, as the recorded average speed seems to decline at longer distances. This is thought to reflect coffee breaks and the like included with the reported time of trips. Finally, we discard 1540 observations with average speed less than 20 km/h. After discarding observations in this way, we are left with 58389 observations for analysis.

The main variables are speed, income and distance. The respondents have stated the time and distance for each trip from which we compute the average speed of the trip. Distance is measured in kilometres and speed is measured in kilometres per hour. Income is the pre-tax income of the driver, deflated to year 2000 prices and measured in 1000 Danish Kroner (DKK). The sample mean income is 243,000 DKK.

Table 1 presents the basic relationship in the data between speed, income and distance. The sample has been split by income into three equal groups (breakpoints at 193,000 and 262,000 DKK). We further split the sample into five distance bands. The table presents the average speed and the number of observations in each group.

		Avg. speed			No. obs.		
Distance	Income	Low	Medium	High	Low	Medium	High
2-10		40.8	41.2	41.8	11755	9488	10707
10-50		56.6	58.2	59.5	7132	7425	8558
50-100		69.7	72.7	76.2	597	615	1232
100-150		79.8	78.9	82.5	144	164	355
150-200		82.5	83.9	87.7	35	56	126

Table 1. Summary statistics: speed, distance and income

A number of points are noted from table 1. First, note that the average speed increases with distance. Trips take place on different types of roads with different speed limits and traffic characteristics. Short trips are likely to have a higher proportion on local urban roads with low speed limits. Also, some time is fixed regardless of the length of the trip such as getting from the front door to the car.

Second, average speed increases with income in each distance band. Third, the difference in average speed from low to high income increases as distance increases. The difference in speed is 1 km/h in the 2-10 km distance band and 5.2 km/h in the 150-200 km distance band. Longer trips are more likely to use motorways, where speeds may vary more. However, the data do not record the choice of route. For the estimation we have a variable where the respondent has stated how large a share of the trip that took place in built-up areas. This is a discrete variable, ranging from 1: Completely in built-up area, to 5: completely in rural area. We use this variable to control for the type of road and the corresponding speed limit.

Fourth, the share with medium or high income increases with longer distances. Or stated in another way: people with higher incomes tend to travel longer. As the average speed generally increases with distance this may confound the effect of income on speed. Hence it is not immediately possible to conclude from the table how strong is the influence of income on speed.

There are other potential confounding factors, as the table does not control for age, sex and other variables, which may influence speed and travel distances. Therefore, we perform an OLS regression of speed on income and distance and control for age, sex, family type (single, couple), the presence of children (yes, no), urbanisation at the residence, the share of the trip in built-up areas and a constant. Table 2 and 3 present some summary statistics for the controls.

Variable	N	Share	Avg. speed	Avg. distance	Avg. income
Women	24007	0.411	45.8	14.6	198.0
Men	34388	0.589	51.7	19.1	275.2
Single	7814	0.133	49.7	17.4	227.1
Couple	50579	0.866	50.0	17.2	246.0
No children	25565	0.432	49.9	18.2	234.5
Children	33566	0.568	50.1	16.6	250.2

Table 2. Summary statistics, binary control variables

From table 2 it is noted that men drive faster than women, they also drive longer distances and have higher incomes. Individuals who are part of a couple also drive faster and have higher incomes, although they drive slightly shorter trips. People with children drive faster and have higher incomes but drive somewhat shorter distances. It seems thus that some of the relationship between speed and income may be explained by sex, family type and the presence of children in the household. Controlling for these variables will tend to reduce the apparent effect of income on speed.

Table 3 presents summary statistics for the variables that are treated as continuous in the analysis. The urbanisation variable is measured on the place of residence. It is a seven point scale categorising the size of cities, ranging from 1 in central Copenhagen to 7 in the countryside. As we have discarded observations with trip ends within the Copenhagen region, the variable starts at 3 corresponding to cities with more than 100,000 inhabitants. The correlations presented in table 3 show that speed decreases with age and increases with decreasing city size and that income is lower in smaller cities. Speed increases as more of the trip takes place outside built-up areas.

Variable	Unit	Average	Median	Pairwise correlations		
				Speed	Distance	Income
Speed	Km/h	49.1	48	1.00	0.57	0.10
Distance	Km	49.1	10	0.57	1.00	0.10
Income	1000 DKK	243	228	0.10	0.10	1.00
Age	Years	43.0	42	-0.09	-0.02	0.03
Urbanisation	1-7 scale	5.3	5	0.11	0.00	-0.10
Built-up area	1-5 scale	3.1	4	0.35	0.27	-0.05

Table 3. Summary statistics, continuous variables

We take the main variables, speed, distance and income, in logarithms in order to reduce variance heterogeneity. The log of speed is regressed on log of income, log of distance and other variables. In order to capture the complicated relationship between speed, distance and income shown in table 1, the regression includes income and income squared, distance and distance squared and also distance interacted with income and income squared. In addition, the regression also includes first- and second order effects of sex, children (yes, no), family type (single, couple), age and age squared, urbanisation and a constant. The model was specified using all second-order interactions and then tested down using hierarchical backwards elimination.

Estimation results are shown in table 4. The first column presents results from an OLS regression. Standard errors are White (1980) heteroskedasticity consistent. The goodness of fit is good with a R^2 of 0.46. However, the White heteroskedasticity test detects significant heteroskedasticity in a regression of the squared OLS residuals on the independent variables. Therefore an auxiliary regression is performed of the squared OLS residuals on all independent variables, first including all two-way interactions from the variables in the original equation including interactions and then reduced by deleting insignificant variables using a significance level of 0.01. Estimation results from this regression are presented in table 5. The predicted squared residuals from this auxiliary regression are used to construct weights for GLS estimation of the original speed equation in the FGLS procedure (Greene, 1993). The results of the FGLS estimation are also included in table 4. All variables are generally quite significant reflecting on the very large number of observations.

Variable	Coefficient	t-Statistic	Coefficient	t-Statistic
Constant	-1.05	-10.8	-1.09	-11.3
Log(distance)	0.38	10.1	0.41	10.7
Log(distance)^2	-0.0058	-5.8	-0.0081	-8.1
Log(income)	0.087	2.3	0.095	2.5
Log(income)^2	-0.0081	-2.1	-0.0090	-2.4
Log(distance)* Log(income)	-0.045	-3.1	-0.048	-3.3
Log(distance)* Log(income)^2	0.0053	3.7	0.0056	3.9
Log(distance)*Female	0.0088	4.2	0.0073	3.5
Age	-0.00067	-3.0	-0.00063	-2.9
Log(distance)*Age	-0.00040	-4.9	-0.00043	-5.3
Female* Age	-0.00058	-4.3	-0.00054	-4.1
Single	-0.047	-4.0	-0.045	-3.9
Urbanisation	0.049	17.4	0.049	17.6
Log(distance)* Urbanisation	-0.0043	-4.7	-0.0056	-6.1
Female*Urbanisation	-0.0052	-4.3	-0.0047	-4.0
Single* Urbanisation	0.010	4.5	0.0094	4.4
Built-up =1	-0.18	-15.2	-0.17	-14.3
Built-up =2	-0.14	-15.6	-0.14	-14.8
Built-up =3	-0.080	-14.7	-0.074	-13.9
Built-up =5	0.081	6.4	0.080	6.4
Log(distance)*(Built-up =5)	-0.0088	-2.3	-0.010	-2.5
Landbo*(built up)	-0.0078	-10.3	-0.0073	-9.8
R-squared	0.46		0.46	

Table 4. Estimation results, OLS and FGLS

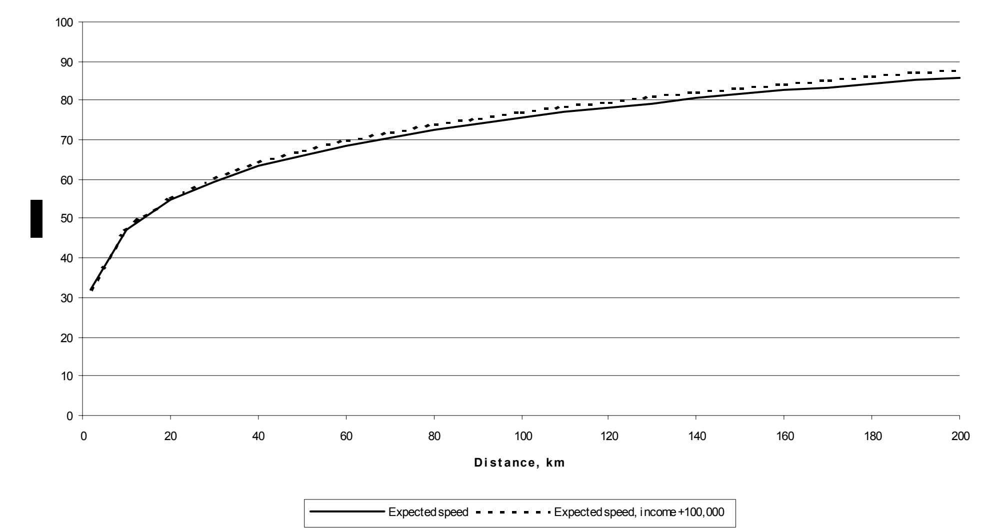

Figure 2. Predicted speed at various distances

The predicted speed using FGLS estimates evaluated at sample means is shown in figure 2. The model predicts an average speed of 32 km/h at the shortest distance increasing to 86 km/h at the longest distances. The figure also includes a line representing the predicted speeds when the income is raised by 100,000 DKK from the sample mean, an increase of close to 40%. This leads to predicted increases in average speed ranging from 0.1 km/h at the shortest distances to 2 km/h at the longest distances.

Income enters the model interacted with distance such that the influence of income on speed depends on trip distance. Income also enters squared such that the derivative of the expected speed depends on income. This accords with the theoretical model, where speed increases roughly with the square root of income. We evaluate the derivative with respect to income at the mean income in the sample, using the FGLS parameter estimates. This is shown in figure 3.

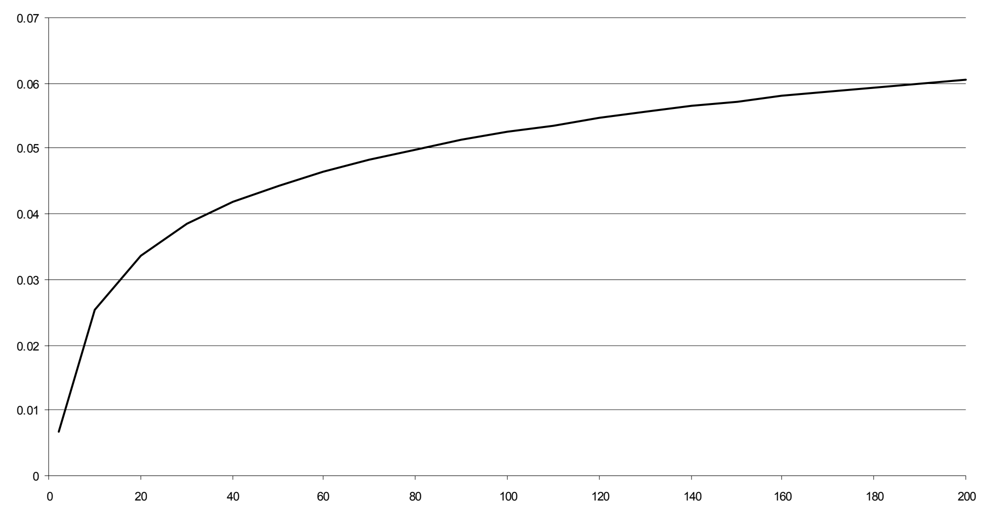

Figure 3. The derivative of log(speed) with respect to log(income)

The empirical results show that the derivative of speed with respect to income increases with distance at a decreasing rate. At the shortest distance an increase in income of 1 percent increases speed by 0.007 percent. At the longest distances, average speed increases by 0.058 percent.

More comments can be applied to the parameter estimates provided here. Generally, the results are as expected. Speed decreases with age, men drive faster than women and the difference increases with distance – at the longest distance men drive 1.7 km/h faster than the average driver while women drive correspondingly slower. Singles drive slightly faster than people who live in couples. Speed increases with decreasing urbanisation, i.e. as the urbanisation index increases, and speed increases when less of the trip takes place in built-up areas.

Variable	Coefficient	t-Statistic
Constant	-0.18	-3.7
Log(distance)	0.15	9.3
Log(distance)^2	-0.035	-19.0
Log(distance)^4	0.00070	22.8
Log(income)	0.11	4.0
Log(income)^2	-0.019	-4.5
(Log(income)^4	0.00012	4.4
Log(distance)* Log(income)	-0.021	-2.7
Log(distance)* Log(income)^2	0.0036	3.6
Log(distance)^2* Log(income)^4	-0.0000058	-5.3
Age	-0.000079	-2.7
Urbanisation^2	0.00063	5.6
Log(distance)* Urbanisation	-0.0041	-4.9
(Log(distance)* Urbanisation)^2	0.000080	5.2
Female* Urbanisation	-0.0010	-6.4
Built-up =5	0.036	8.4
Log(distance)*(Built-up =5)	-0.0078	-5.3
(Urbanisation *Built-up)^2	-0.000024	-10.1
R-squared	0.023	

Table 5. Estimation results, auxiliary regression of variances

Concluding remarks

We have employed a simple micro-economic model where a consumer attaches a value to time and risks receiving a fine with some probability. This is sufficient to drive the results that speed increases with income and decreases if the probability or the size of a fine increases. Increasing the speed limit also raises speed. We have indicated how the model can be extended to allow for speed dependent fuel consumption and the quality of the car.

Using a large cross-sectional dataset we have shown that the effect of income on speed is also observable in practice with quite noticeable effects. Thus income growth is likely to be an important factor behind the observed general increase in motorway speeds. According to this explanation, increasing incomes have increased the perceived value of time and decreased the effect of fines, which in turns has lead to increased speeds. This trend must then be expected to continue, unless enforcement is strengthened.

When speed depends on income it is questionable to include both speed and income as independent variables in single equation time series models for road accidents, as the speed variable is likely to include an income effect. This reflects on a number of previous studies as discussed in the introduction.

According to the theoretical model, the effect of income on speed occurs because the value of time increases with income whereas the fine does not. It is clearly possible to neutralise the effect of income on speed by letting the size of the fine increase with income as well. In order to investigate this relationship we let the fine be a function of income, F=F(w), and differentiate (1) with respect to income, demanding that $\partial S / \partial w = 0$. The resulting equation can be rearranged as

$$\frac{\partial \log F}{\partial w}(w) = \frac{1}{1 - \gamma F(w)(S - S_0)}.$$

Noting that $\gamma<0$ by assumption, the derivative is seen to be positive and less than 1. A fine that increases with income but less than proportionally would thus ensure that all travel at the same speed in our model. A pragmatic alternative would be to rely more on non-monetary sanctions such as withdrawal of the driving licence.

References

- Danmarks Statisk (2000) Transport 2000.
- Danmarks Statistik (2003) Adam databanken. www.dst.dk.
- Danmarks TransportForskning (2002) Notat, 130 km/t på motorveje.
- Danmarks TransportForskning (2003) Transportvaneundersøgelsen, www.dtf.dk/tu.
- Dansk Politi. Annual report, various years.
- Birkeland, M and Fosgerau, M. (1999) Personbilers Energieffektivitet. Trafikdage på Aalborg Universitet, www.trafikdage.dk.
- Gander, J.P. A utility-theory analysis of automobile speed under uncertainty of enforcement. Transportation Research Part B. Vol. 19, Issue 3, June 1985, 187-195.
- Greene, W.H. (1993) Econometric Analysis second edition, Prentice Hall, New Jersey.
- Hakim, S. and Shefer, D. (1991) A critical review of macro models for road accidents. Accident Analysis and Prevention Vol. 23 No. 5, 379-400.
- Ortúzar, J. de D. and Willumsen, L.G. (1994) Modelling Transport, second edition. John Wiley & Sons Ltd.
- Scuffham, P.A. and Langley, J.D. A model of traffic crashes in New Zealand. Accident Analysis and Prevention 34 (2002) 673-687.
- Shinar, D., Schechtman, E. and Compton,R. Self-reports of safe driving behaviors in relationship to sex, age, education and income in the US adult driving population. Accident Analysis and Prevention 33 (2001) 111-116.
- Vejdirektoratet (1996) Hastighedsrapport. Rapport nr. 49.
- Vejdirektoratet (2000) Hastighedsrapport. Rapport nr. 202.
- White, H. (1980) A Heteroskedasticity-Consistent Covariance Matrix and a Direct Test for Heteroskedasticity, Econometrica, 48, 817-838.
- Zlatoper, T.J. (1991) Determinants of motor vehicle deaths in the United States. Accident Analysis and Prevention Vol. 23 No. 5, 431-436.