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Abstract

The relationship between speed and income is established in a microeconomic model focusing on the trade-off between travel time and the risk of receiving a penalty for exceeding the speed limit. This is used to determine when a rational driver will choose to exceed the speed limit. The relationship between speed and income is found again in the empirical analysis of a cross-sectional dataset comprising 60,000 observations of car trips. This is used to perform regressions of speed on income, distance travelled, and a number of controls. The results are clearly statistically significant and indicate an average income elasticity of speed of 0.02; it is smaller at short distances and about twice as large at the longest distance investigated of 200 km.

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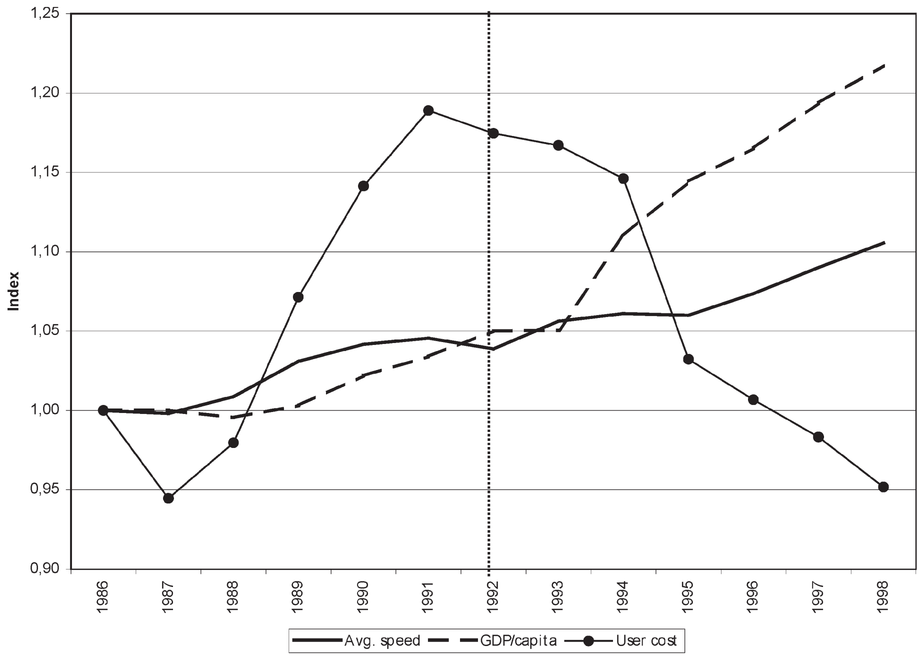
1.0 Introduction

1.1 Increasing speeds

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 began. 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 something 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

Figure 1
The Average Speed on Danish Motorways, Real GDP Per Capita and User Cost of Car Use



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).

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 the 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, other things being equal. 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, for example, in Birkeland and Fosgerau (1999). Rienstra and Rietveld (1996) find a significant relationship between income and the maximum speed of the car, whereby not only the higher income groups have faster cars but also the low income group.

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). Until 1991 the user cost index had increased by 19 percentage points, followed by a long decrease of 24 percentage points until 1998. It is likely that this development has also 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 microeconomic model and then validate the relationship using a large cross-sectional dataset.

1.2 Literature review

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 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 macromodels 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. Rietveld and Shefer (1998) discuss speed limits and fines as a means to correct for externalities. They consider specifically the case of heterogeneous drivers with different optimal speeds, but do not analyse the cause of these differences.

Empirical results on the relationship between speed and income are hard to come by. Some results 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. Rienstra and Rietveld (1996) find similar results. In contrast to both Shinar *et al*. and Rienstra and Rietveld 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.

This paper proceeds 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 use a large microdataset from the Danish national travel survey. Finally, Section 4 contains some concluding remarks.

2.0 Theoretical Analysis

2.1 The model

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 non-positive, implying that the consumer is risk-averse or risk-neutral. Disregarding leisure, he spends his total time allocation T on work and travel only. We assume an increasing and convex speed dependent fuel consumption of $f(S)$. With a fixed driving distance normalised to 1 and travel speed S, the time spent travelling is $1/S$. Given the wage rate w as a value of time, the income available for consumption is $w(T-1/S)-f(S)$.

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 $CF(S-S_0)$, where F is the fine per km/h over the speed limit. This is the structure of fines in Denmark. Like Gander, we assume for simplicity that $S > S_0$, that is, 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,

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

Substitute this into the utility function to achieve $V(S,C) = U(X(S,C))$. 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. Using the partial derivative of V with respect to speed, $V_S(S,C) = U_X(X(S,C))(w/S^2 - f_S(S) - CF)$, we compute the first order condition for maximum as

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

Solving this with respect to S results in

$$\begin{aligned} 2\log S = {} & \log(w) + \log[\pi U_X(X(S,1)) + (1-\pi)U_X(X(S,0))] \\ & - \log[\pi U_X(X(S,1))(f_S(S)+F) + (1-\pi)U_X(X(S,0))f_S(S)]. \end{aligned}$$

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

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

Introduce the notation $\gamma = -X(S,1)U_{XX}(X(S,1))/U_X(X(S,1))$ and note that $\gamma \geqslant 0$ since the utility function is increasing and concave. We assume for simplicity that γ is constant. This condition is satisfied, for example, for $U(X) = \log(X)$ or $U(X) = X^{1/2}$. With this notation we have

$$2\log S = \log\left(\frac{w}{\pi F + f_S(S)}\right) - \gamma\frac{F(S - S_0)}{X(S,1)}. \tag{1}$$

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

$$\begin{aligned} 2\frac{\partial \log S}{\partial \log w} = {} & 1 - \frac{\gamma F S}{X(S,1)}\frac{\partial \log S}{\partial \log w} + \frac{\gamma F(S - S_0)}{X(S,1)}\frac{\partial \log X(S,1)}{\partial \log w} \\ & - \frac{f_{SS}(S)S}{\pi F + f_S(S)}\frac{\partial \log S}{\partial \log w}, \end{aligned}$$

$$\frac{\partial \log S}{\partial \log w} = \frac{X(S,1) + \gamma F(S - S_0)\dfrac{\partial \log X(S,1)}{\partial \log w}}{2X(S,1) + \gamma F S + \dfrac{S f_{SS}(S) X(S,1)}{\pi F + f_S(S)}} > 0.$$

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, when the speed limit increases, and when the price of fuel consumption increases.

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 ($\pi = 0$).

2.2 When to drive too fast

The model assumes that the driver always exceeds the speed limit. It is quite possible to relax this assumption in order to investigate the conditions for this choice. First, observe that when disregarding other costs, the model shows that the consumer will always drive at or above the speed limit. The speed limit will be violated when $2\log(S_0) < \log(w/\pi F)$ or when $\pi < w/S_0^2 F$. That is, the consumer will violate the speed limit when the probability of getting caught is less than the hourly pre-tax wage divided by the speed limit squared and the fine per kilometre per hour.

Using current Danish figures provides some indication on the influence of fines on speeds. With $S_0 = 110\,\text{km/h}$, $w = 72\,\text{kr/h}$ (the sample mean in the empirical section, using an average tax rate of 50 per cent and 1,680 working hours per year), $F = 54\,\text{kr/(km/h)}$, which is the current rate on Danish motorways, it is found that $\pi < 1/7{,}600$ will make a rational driver with average income exceed the speed limit. This can be compared to the 4,780 million kilometres driven annually on Danish motorways (DTF, 2002) and the 9,000 cases of speed limit violations recorded annually by the Danish police on motorways (Rigspolitichefen, 2000).[1] This corresponds to a rate of about 1/500,000. Thus, it is no surprise that the average speed on Danish motorways is considerably above the speed limit.

2.3 Income dependent fines

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. Let the fine be a function

[1]The latter figure comprises most cases though not all.

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 to show that $\partial \log F/\partial \log w(w) = 1$, when the effect of speed dependent fuel consumption is disregarded. A fine that increases proportionally with income would thus ensure that all travel at the same speed in our model, except for the correction due to fuel consumption.

3.0 Empirical Results

3.1 Data

For the empirical test of the relationship between speed and income we use 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 76,001 observations. We further discard 15,846 observations of trips below two 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 so on included with the reported time of trips. Finally, we discard 1,539 observations with average speed less than 20 km/h and a few other observations with missing values. This leaves 58,385 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 1,000 Danish Kroner (DKK).[2] 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 270,000 DKK). We further split the sample into five distance bands. The table presents the average speed and the number of observations in each group.

[2]The current exchange rate is €100 = 743 DKK.

Table 1
Summary Statistics: Speed, Distance and Income

	Average Speed			Number of Observations		
	Income			Income		
Distance	Low	Medium	High	Low	Medium	High
2–10	40.8	41.3	41.7	11,755	10,088	10,707
10–50	56.6	58.2	59.6	7,132	7,984	7,999
50–100	69.7	72.9	76.2	597	646	1,201
100–150	79.8	78.4	82.8	144	172	347
150–200	82.5	83.7	88.0	35	61	121

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 0.9 km/h in the 2–10 km distance band and 5.5 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 with five levels, ranging from ‘‘Completely in built-up area’’ to ‘‘Completely in rural area’’. We use this variable to control for the type of road and the corresponding speed limit.

Fourth, the proportion 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 regressions 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

Table 2
Summary Statistics: Binary Control Variables

Variable	*N*	*Share*	*Avg. speed*	*Avg. distance*	*Avg. income*
Women	24,005	0.41	47.6	14.6	198.0
Men	34,386	0.59	51.6	19.1	275.2
Single	7,816	0.13	49.7	17.4	227.1
Couple	50,575	0.87	50.0	17.2	246.0
No children	24,828	0.43	49.8	18.2	234.4
Children	33,563	0.57	50.0	16.6	250.2
Res. in Central Copenhagen	61	0.00	52.8	25.5	286.8
Res. in Greater Copenhagen	70	0.00	55.2	34.5	351.4
Res. in city >100,000 inh.	5,926	0.10	45.0	16.3	261.2
Res. in city 10–100,000 inh.	12,808	0.22	47.2	16.2	254.5
Res. in city 2–10,000 inh.	11,065	0.19	52.2	19.0	250.5
Res. in city 200–2,000 inh.	10,945	0.19	52.2	18.4	236.0
Res. in rural area	17,512	0.30	50.7	16.4	229.2
Trip completely in built-up area	12,792	0.22	40.0	7.4	251.2
Trip mainly in built-up area	5,488	0.09	44.5	11.2	255.8
Trip equally in built-up and rural area	7,383	0.13	50.3	17.4	238.9
Trip mainly in rural area	27,359	0.47	54.9	22.6	239.9
Trip completely in rural area	5,367	0.09	53.5	19.7	236.9

the trip in built-up areas, and a constant. Tables 2 and 3 present some summary statistics for the controls.

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

Table 3
Summary Statistics: Continuous Variables

				Pairwise correlations		
Variable	*Unit*	*Average*	*Median*	*Speed*	*Distance*	*Income*
Speed	Km/h	49.9	48	1.00	0.57	0.10
Distance	Km	17.3	10	0.57	1.00	0.10
Income	1,000 DKK	243	228	0.10	0.10	1.00
Age	Years	43.0	42	−0.09	−0.02	0.03

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. We note that speed decreases with age.

3.2 Empirical model estimation

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 control variables, which are sex, family type (single, couple), age, urbanisation dummies, dummies for the share of the trip in built-up areas, year dummies, and a constant. A potential selection bias is controlled for by inclusion of the inverse Mills ratio from a binary probit model estimated on the whole survey material for the probability of occurring in the sample for this model (Wooldridge, 2002). We estimate four models, all with White heteroskedasticity consistent standard errors. Model 1 is an OLS with main effects only. One may worry that endogeneity of distance may bias results and this is also the result of a Hausman test. Therefore model 2 is a 2SLS version of model 1 where area dummies dividing Denmark into 263 municipalities have been used as instruments for distance. In order for these to be valid instruments, they must be correlated with distance but not with the error of the estimated equation. This is arguably the case, since distances are different in the specified regions and since the variable for a built-up area captures the type of road used, which has a separate effect on speed. In model 3 we include the area dummies directly into the model and estimate by OLS. Model 4 is intended to capture more of the complicated relationship between speed, distance, and income shown in Table 1. This model includes income and income squared, distance and distance squared, and also distance interacted with income and income squared. In addition, model 4 includes interactions with the controls. The model was specified using all second-order interactions and then tested down using hierarchical backwards elimination, which is to say that insignificant first-order effects are not deleted if they occur in a second-order effect. Model 4 is estimated by OLS since the interactions with distance makes it quite difficult to use 2SLS.

The estimation results are shown in Table 4. The goodness of fit is good with R-squares of around 0.46. All variables are generally quite significant reflecting on the very large number of observations. The t-statistic for the inverse Mills ratio acts a test for selection bias (Wooldridge, 2002), and is not significant in any of the models, indicating that selection bias has little effect.

Table 4
Estimation Results

	Model 1 OLS	*Model 2 2SLS*	*Model 3 OLS with area dummies*	*Model 4 Interactions*
Constant	−0.75 (−65)	−0.67 (−29)	−0.85 (−61)	−0.92 (−10)
Log(distance)	0.22 (182)	0.19 (21)	0.22 (181)	0.35 (9.4)
Log(income)	0.021 (11)	0.024 (12)	0.023 (13)	0.082 (2.1)
Female	−0.033 (−15)	−0.038 (−15)	−0.033 (−15)	−0.028 (−2.8)
Single	0.0031 (1.02)	0.0038 (1.2)	0.0018 (0.59)	0.012 (3.2)
Age	−0.0018 (−23)	−0.0019 (−23)	−0.0018 (−23)	−0.0373 (−3.2)
Res. in Central Copenhagen	−0.059 (−1.5)	−0.051 (−1.3)	−0.057 (−0.72)	−0.019 (−0.36)
Res. in Greater Copenhagen	−0.082 (−3.3)	−0.062 (−2.4)	0.15 (18)	−0.20 (−3.2)
Res. in city >100,000 inh.	−0.074 (−17)	−0.0602 (−11)	−0.0084 (−1.3)	−0.067 (−3.9)
Res. in city 10–100,000 inh.	−0.026 (−8.3)	−0.017 (−4.7)	−0.0070 (−1.7)	−0.071 (−7.5)
Res. in city 2–10,000 inh.	0.0042 (1.4)	0.014 (3.7)	0.015 (4.6)	−0.029 (−3.5)
Res. in city 200–2,000 inh.	0.0079 (2.7)	0.014 (4.3)	0.0072 (2.4)	0.015 (3.9)
Res. in rural area	–	–	–	–
Trip completely in built-up area	−0.075 (−22)	−0.11 (−11)	−0.065 (−19)	−0.049 (−10)
Trip mainly in built-up area	−0.062 (−15)	−0.087 (−12)	−0.051 (−12)	−0.051 (−12)
Trip equally in built-up and rural area	−0.035 (−11)	−0.045 (−11)	−0.030 (−9)	−0.037 (−11)
Trip mainly in rural area	–	–	–	–
Trip completely in rural area	0.012 (3.3)	0.0065 (1.6)	0.011 (2.95)	0.0089 (2.1)
Year = 1997	0.0065 (1.8)	0.0082 (2.3)	0.0060 (1.7)	0.0070 (2.0)
Year = 1998	0.0464 (0.018)	0.0013 (0.37)	−0.0351 (−0.14)	0.0322 (0.062)
Year = 1999	−0.0035 (−0.99)	−0.0019 (−0.53)	−0.0032 (−0.89)	−0.0032 (−0.9)
Year = 2000	0.016 (4.6)	0.019 (5.2)	0.018 (4.97)	0.016 (4.5)
Year = 2001	−0.0024 (−0.67)	−0.0344 (−0.12)	−0.0015 (−0.42)	−0.0020 (−0.55)
Inverse Mills ratio	−0.0055 (−1.6)	−0.0062 (−1.8)	−0.0051 (−1.5)	−0.0052 (−1.5)
Log(distance)^2				−0.0063 (−6.3)
Log(income)^2				−0.0076 (−2.0)
Log(distance) × log(income)				−0.045 (−3.1)

Log(distance) × log(income)^2				0.0052 (3.6)
Log(distance) × female				0.0091 (3.8)
Log(distance) × age				−0.0339 (−4.8)
Female × age				−0.0352 (−3.1)
Log(distance) × (Res. in Greater Copenhagen)				0.050 (2.5)
Log(distance) × (Res. in city >100,000 inh.)				0.016 (3.2)
Log(distance) × (Res. in city 10–100,000 inh.)				0.021 (6.8)
Log(distance) × (Res. in city 2–10,000 inh.)				0.011 (3.7)
Female × (Res. in city 200–2,000 inh.)				−0.018 (−3.5)
Single × (Res. in Central Copenhagen)				−0.18 (−2.5)
Single × (Res. in Greater Copenhagen)				−0.14 (−2.2)
Single × (Res. in city >100,000 inh.)				−0.029 (−3.0)
Single × (Res. in city 10–100,000 inh.)				−0.017 (−2.5)
(Res. in Central Copenhagen) × (Trip completely in built-up area)				0.23 (3.1)
(Res. in Greater Copenhagen) × (Trip completely in built-up area)				−0.12 (−2.8)
(Res. in city >100,000 inh.) × (Trip completely in built-up area)				−0.073 (−6.5)
(Res. in city 10–100,000 inh.) × (Trip completely in built-up area)				−0.021 (−2.8)
(Res. in city >100,000 inh.) × (Trip mainly in built-up area)				−0.078 (−6.2)
(Res. in city 10–100,000 inh.) × (Trip completely in rural area)				−0.023 (−2.0)
(Res. in city 200–2,000 inh.) × (Trip completely in rural area)				0.042 (4.0)
Area dummies	–	–	not shown	–
R-squared	0.47	0.46	0.48	0.470

3.3 Results

Model 1 estimates an income elasticity of 0.021 with a high level of significance. In model 2 instruments are used to control for endogeneity of distance. Since there is only one variable that may cause endogeneity bias, it is possible to determine the direction of bias. It is likely that the error in the speed equation will be positively correlated with the error in an equation for distance. This would lead to a too high parameter estimate for distance and hence the effect of speed on income is probably underestimated. The endogeneity bias is, however, likely to be small. The time cost of a trip increases with income and the compensation for this by higher speed is relatively small. The results from model 2 bears this reasoning out with an estimated income elasticity of 0.024, again estimated with a high level of significance. Model 3 shows similar results with an estimated income elasticity of 0.023, which is again very significant.

Model 4 predicts an average speed of 32 km/h at the shortest distance increasing to 87 km/h at the longest distances. The predicted speed increases with distance at a decreasing rate. 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. We evaluate the income elasticities of speed at the sample average income and at various distances, using the parameter estimates of model 4, where the elasticities are found as the derivative of log(speed) with respect to log(income) and standard errors are calculated using the estimated covariance matrix. The results indicate that the income elasticity of speed increases with distance at a decreasing rate. At the shortest distance the elasticity is 0.007 with a standard error of 0.003. This elasticity is statistically significantly different from zero with a *t*-value of 2.8. At the sample average log(distance) the income elasticity is 0.026 (0.003), which is slightly more than in models 1–3. At the longest distances, the elasticity is 0.058 (0.002), which is highly statistically significant. The elasticity estimates are probably downward biased, as were model 1 compared to model 2. The elasticities in model 3 translate into speed differences between the 10 and 90 per cent income percentiles of 0.2 km/h at 2 km to 4.5 km/h at 200 km. This is consistent with Rienstra and Rietveld (1996), who find that the effect of income on speed limit transgression behaviour is more significant on roads with higher speed limits, when considering that roads with high speed limits are more likely to be used on longer trips.

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, singles drive slightly faster than people who live in couples, speed increases with decreasing urbanisation, that is, as the urbanisation index increases, and speed increases when less of the trip takes place in built-up areas.

4.0 Concluding Remarks

We have employed a simple microeconomic 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. The model allows for speed dependent fuel consumption and we have indicated how the model can be extended to allow for the quality of the car. Moreover, we have shown how an income dependent fine could approximately neutralise the effect of income on speed. A pragmatic alternative would be to rely more on non-monetary sanctions such as withdrawal of the driving licence.

The model assumes for simplicity that the driver always exceeds the speed limit, which is true for the majority on Danish motorways. This fact could suggest that other marginal speed dependent costs are low. Disregarding other speed dependent costs for a moment, the speed limit will be violated when the probability of getting caught is low, that is, when $\pi < w/S_0^2F$. Using current Danish figures we have indicated that the present rate of detection is much too low for a rational driver with average income to observe the speed limit on motorways.

A criticism of the theoretical analysis may be that drivers do not have consistent estimates of the probability of getting caught. There does in fact exist a plausible mechanism whereby drivers can assess this probability. By using the model presented, a rational driver can infer the probability estimates of other drivers from their choice of speed. Combining these with his own experience of getting caught results in consistent estimates for each individual. On average these estimates depend only on the number of fines presented.

4.1 Empirical results

Using a large cross-sectional dataset we have shown that the effect of income on speed is also observable in practice with quite noticeable and highly statistically significant effects. The effect is consistently present when the model allows for endogeneity of distance, when a large number of area dummies is used, and when the model allows for a more complex relationship with many interactions. It is likely that the observed effect would be larger if we were able to observe the type of road and the speed limit, since we expect that speed variation is higher on motorways and roads with higher speed limits (Rienstra and Rietveld, 1996).

When there is a cross-sectional relationship between speed and income, it is also likely that income growth is 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 and other speed dependent user costs, which in turn has lead to increased speeds. The effect may be larger in the aggregate than the cross-sectional data show, since aggregate behaviour may influence individual behaviour, for example if the risk of receiving a fine is not constant but larger for individuals driving at speeds in excess of the average.

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