Denne artikel er publiceret i det elektroniske tidsskrift
Artikler fra Trafikdage på Aalborg Universitet
(Proceedings from the Annual Transport Conference
at Aalborg University)
ISSN 1603-9696
www.trafikdage.dk/artikelarkiv

Weather and road capacity

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Abstract

The paper presents estimations of the effect of bad weather on the observed speed on a Danish highway section; *Køge Bugt Motorvejen*. The paper concludes that weather, primarily precipitation and snow, has a clear negative effect on speed when the road is not in hypercongestion mode. Furthermore, the capacity of the highway seems to be reduced in bad weather and there are indications that travel time variability is also increased, at least in free-flow conditions. Heavy precipitation reduces speed and capacity by around 5-8%, whereas snow primarily reduces capacity. Other weather variables such as darkness, frost, wind and fog also have effects, but they are minor and are hard to assess exactly. In general, the effects are less than found in other studies, primarily from North America. The effects are estimated using a two-step procedure. In step 1 the log to travel time is regressed non-parametrically against traffic density and in step 2 the residuals from step 1 are regressed linearly against the weather variables. The choice of a non-parametric method is made to avoid constricting ties from a parametric specification and because the focus here is not on the relationship between traffic flow and speed.

Introduction
Future climate changes are expected to lead to less stable weather with more frequent rainstorms. Also winter temperatures are expected to go up, implying less frequent snowfall. Such weather events affect road traffic, and climate change is therefore expected to change future road conditions such as speed and road capacity. To assess the effect of climate change, knowledge is needed on how various weather components affect the relation between speed, flow, and density on the road.

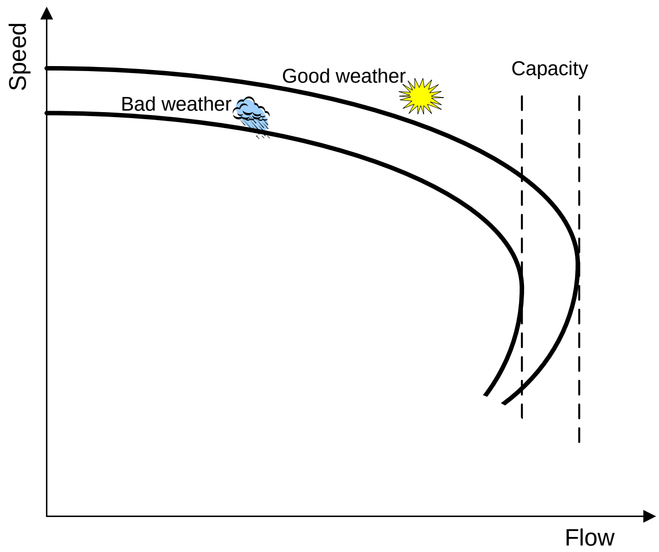
The purpose of the analyses presented here is to find out if and how the weather affects the speed-flow curve. For this purpose, data for the highway *Køge Bugt Motorvejen* are applied. The highway is one of the main gateways for Copenhagen.

It is expected that the weather may affect the driving conditions negatively through three factors, visibility, road conditions and driving stability:

1.	Visibility	Fog, precipitation, darkness/daytime, light reflections
2.	Road conditions	Water, snow, frost, ice storm, dirt, leaves
3.	Stability	Gusts of wind

These factors may affect speed in different ways. Bad visibility may for instance affect speed when the density is low, but if the density is high it could mean less, and bad road conditions may mainly be important when the speed is high. Furthermore, bad weather may affect not only the average speed, but also travel time variability which is considered a cost for travellers in line with the expected travel time.

It is expected that bad weather reduces both the speed for a given traffic flow and the maximum flow (capacity) of the road as depicted in the speed-flow curves below.



Literature review
The literature has mainly dealt with the effect on speed from rain and snow, but also visibility, wind, and frost have been analysed. A few studies have been using measurements of the road surface conditions (Hranac et al, 2006) and some include the effect from daylight versus night (Brilon and Ponzlet, 1996). Most studies use data from nearby meteorological stations or airports, but there are also studies using radar precipitation data (Dailey, 2006).

The size of the weather effects found varies, but for rain the reduction in speed is typically measured to be around 10% (Unrau and Andrey, 2006, Perrin et al., 2001, Hranac et al. (2006), Brilon and Ponzlet (1996) Ibrahim and Hall (1994)). Others (Maze et al., 2006 and Alhassan and Ben-Edigbe, 2011) find lower effects of around 5%. Hranac et al (2006) and Ibrahim and Hall (1994) distinguish between light and heavy rain and they find that light rain has an effect on speed of a little more than half the effect from heavy rain.

The effect from snow is reported both as snowfall and snow on the surface. Maze et al (2006) reports 4-13% and Hranac et al (2006) 5-16% speed reduction from snowfall, and Perrin et al. (2001) report 20-25% speed reduction from slushy conditions. Maze et al. (2006) include visibility and frost and conclude that low visibility reduces speed by 7-12% though there is no clear evidence that fog reduces speed more than haze. They find that frost has only clear effects when temperatures drop to around -20°C and wind only reduces speed by 1-2%. Brilon and Ponzlet (1996) find a speed reduction of around 4% at night compared to daytime.

There are somewhat conflicting results on how the weather effects depend on the traffic flow. Ibrahim and Hall (1994), Unrau and Andrey (2006) and Hranac et al. (2006) find that rain dampens traffic speed more when the flow is high (though not in hypercongested where the effect from rain is low) whereas Brilon and Ponzlet (1996) find the opposite when comparing free-flow and partly dense conditions. The conclusions in the former studies may be dependent on the simple linear or quadratic specification of the speed-flow curve though.

Some few studies use data sufficient to analyze the weather effect in hypercongested conditions. Unrau and Andrey (2006) find that the effect on speed from rain are smaller (in relative terms) in hypercongestion. The model in Hranac et al. (2006) has the property that the effect from bad weather diminishes when density is approaching jam density.

Some of the studies mentioned use data showing increasing speed variability in bad weather (e.g. Alhassan and Ben-Edigbe (2011), but travel time variability is seldom touched upon.

Estimates of reductions in road capacity due to bad weather are also found in the literature. Hranac et al (2006) finds capacity reductions of around 10% for rain and 12-20% for snow through estimation of correction factors to calibrated flexible, non-linear specifications of the speed-flow and speed-density curves. Maze et al. (2006) estimate the capacity reductions to be 2-14% for rain and 4-22% for snow through a simple method computing the average of the 5% highest flow observations in good and bad weather. In this way they probably mix up the effect on capacity and the drop in demand that bad weather often implies. There are more attempts to measure the effect on capacity, but they are often based on data with no hypercongestion combined with assumptions on the shape of the speed-flow curve.

Some of the above mentioned papers address directly the question how the flow is affected by the weather. The inflow may be reduced in bad weather either by reduced demand or by increased congestion at the entries or preceding sections of the road and in practise it is hard to distinguish between the two. The flow effect is probably highly dependent on local conditions. Alhassan and Edigbe (2011) measure a flow reduction of 8½% during rain on a principal road in Malaysia, but do not distinguish between demand effects and supply effects.

The methodological approaches to the speed-flow or speed-density curves' dependency on the weather vary a lot. The most common approaches are:

- Taking the mean speed in good and bad weather or categories of weather and comparing the two (e.g. Maze et al., 2006, Brilon and Ponzlet, 1996).
- Estimating linear or quadratic speed-flow (or travel time-density) curves in good and bad weather and comparing (Unrau and Andrey, 2006, and partly Alhassan and Ben-Edigbe, 2011).

- Estimating speed or flow curves using a specification including weather variables (parametric). Examples are Ibrahim and Hall (1994). Hranac et al (2006) who apply the four-parameter van Aerde specification of the speed-flow curve is another example.
- Non-parametric estimation is commonly used when estimation speed-flow curves, but apparently no-one has used it in connection with weather variables. For instance, Oswald et al (2001) use nearest neighbour nonparametric regression methods.
- Other methods include Huang and Ran (2003) who apply a neural network methodology to predict highway speeds in the very short term using detailed weather forecasts. Einbeck (2007) models a speed-flow curve in several ways, one them being principal curves using local centres of mass along the curve, thus overcoming the problem that the curve has two speed values for each value of flow, but does not relate to the effect of weather.

Data

Observations of the traffic on the Køge Bugt Highway in the direction towards the city centre (i.e. heading northeast) are used in the estimations. The speed limit is 110 km/h all the way. The highway is separated into 8 segments. Below, the segments are defined and showed on a map.

Overview of the segments

Segment	Start	End	Lanes
1	exit 32	exit 31	3
2	exit 31	exit 30	3
3	exit 30	exit 29	3
4	exit 29	exit 27	4
5	exit 27	Ishøj (M4)	4-5-3
6	Ishøj (M4)	exit 25	3
7	exit 25	Avedøre (M3)	3-2
8	Avedøre (M3)	exit 22	2-3

Map based on Eniro.dk

Data are made up of speed and flow observations (and derived density) for each segment from the Danish Road Directorate, weather observations from four nearby weather/snow stations from the Danish Meteorological Institute, and the time of sunrise and sunset in the area combined with data for the duration of civil twilight depending on the time of year. Data are harmonized to the frequency of four observations per hour and cover the years 2012-2013, but with periods of missing data. All traffic data are converted to describe traffic per lane. Thus, with no observations missing there would be approximately 70,000 observations for each segment. The traffic data are averaged over the stretch of each segment and over 15 minutes of time.

The weather data are described in more detail elsewhere (can be obtained from author). Unfortunately, the weather observations don't cover all of the above listed weather conditions. Most important, there is no information on the type of precipitation. The available data cover precipitation intensity, wind speed, visibility, temperature 2 meters above the ground, temperature at the ground and snow depth on the ground. For each segment data from the closest station is used. In general weather data are uncorrelated with traffic flow, but darkness and temperature have correlation coefficients with the flow of around -0.30 and 0.09. This is because traffic is concentrated at daytime and temperatures are correlated with the time of day. In the table below the correlation coefficients between flow/density and the weather variables for all 8 segments as a whole are shown:

Correlation coefficients

	Mean flow	Density
Darkness (yes/no)	**-0.2991**	**-0.2166**
Temperature at 2m (°C)	**0.0777**	**0.0264**
Temperature at ground level (°C)	**0.0961**	**0.0385**
Snow depth (cm)	**-0.0196**	**0.0117**
Precipitation intensity (mm/h)	-0.0009	**0.0105**
Visibility (m)	**0.0127**	**-0.0275**
Wind Speed (m/s)	**0.0160**	**-0.0072**

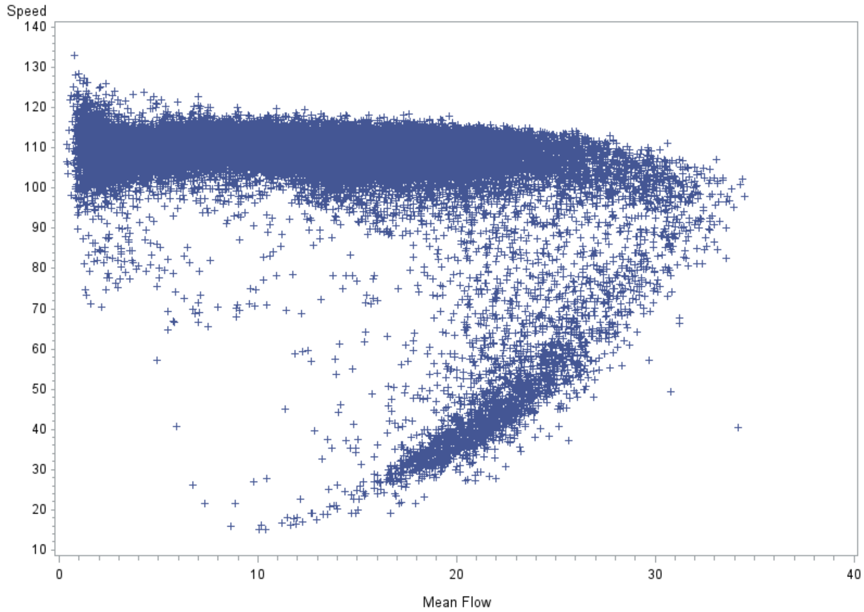
Bold numbers are significant at 1% level.

Before estimation, some observations are omitted:

- Night time observations (10 pm to 4 am, i.e. around 17,500 observations per segment are removed). At night reliability of data is low because of too little flow.
- Periods with incidents (road construction and the like). On average 5,000 observations per segment are dropped.
- Speed below 15 km/h – the loops in the road cannot detect low speeds with high reliability. 230 observations are dropped – they occur in all 8 segments.
- Mean flow larger than 40 vehicles per lane per minute which is clearly above capacity. 1 observation in each of the segments 3 and 4 are dropped.

In this note, only the three first (southern) segments are used. The rest of the segments either have no hypercongestion or displays peculiar shifts in average speed over time. The chosen segments have 3 lanes and no street lighting and they each start and end at a point with entry/exit ramps with no entries/exits along the segment. Flow and speed are measured by loops [Oops, how many and where?]. All three segments clearly have periods of hypercongestion so that the effect on capacity can be analysed. The number of included observations is 39.789 for segment 1, 23.615 for segment 2 and 21.380 for segment 3. The two latter have fewer observations since the data series stop by May 2013. For these three segments, all weather data stems from Roskilde Airport, except for snow depth stemming from Roskilde Town. This means that the weather observations are made 7-17 km from the road segments.

Below, the speed-flow curve from segment 1 (after the omissions listed above) is shown. There are clearly observations with hypercongestion.

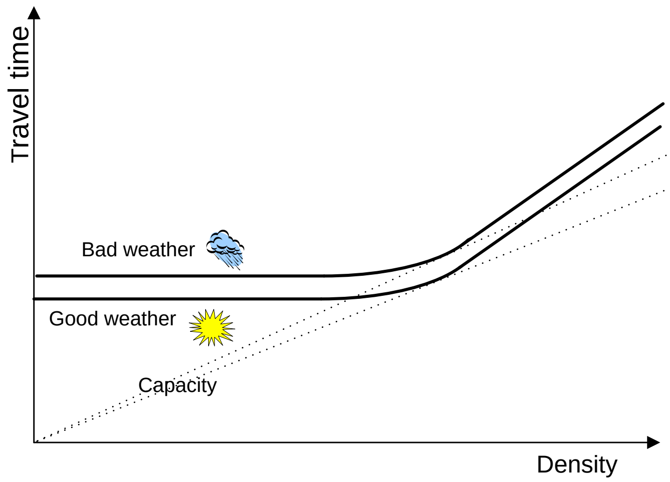


A. Estimation of travel time against density

The speed-flow curve may have two possible speeds for high flow with low and high densities respectively and is therefore immediately suited for estimation. Instead it is chosen to estimate travel time as a function of density using the fundamental of identity of traffic

$$\text{Flow} \equiv \text{speed} \cdot \text{density}$$

Since travel time is the inverse speed, the speed-flow curve can be converted to the following figure.



There are many observations in the data with extraordinary high travel times and few with extraordinary low travel times. Therefore, the log transformation of travel time is used to make the error distribution more symmetric and this also reduces heteroscedasticity.

Since the weather data and traffic data are almost orthogonal, it is possible to split the estimation procedure in two steps without introducing bias:

1. Estimation of log(travel time) on traffic density using a non-parametric method.
2. The residuals from step 1 are used in a linear regression against the weather variables. Here, the estimations are split into density intervals to see if weather has different impact on the speed depending on the density. The specification of step 2 is:

$$\text{Travel time residual}_i = \alpha + \sum_{j=1}^{k} \beta_j X_{j,i} + \varepsilon_i$$

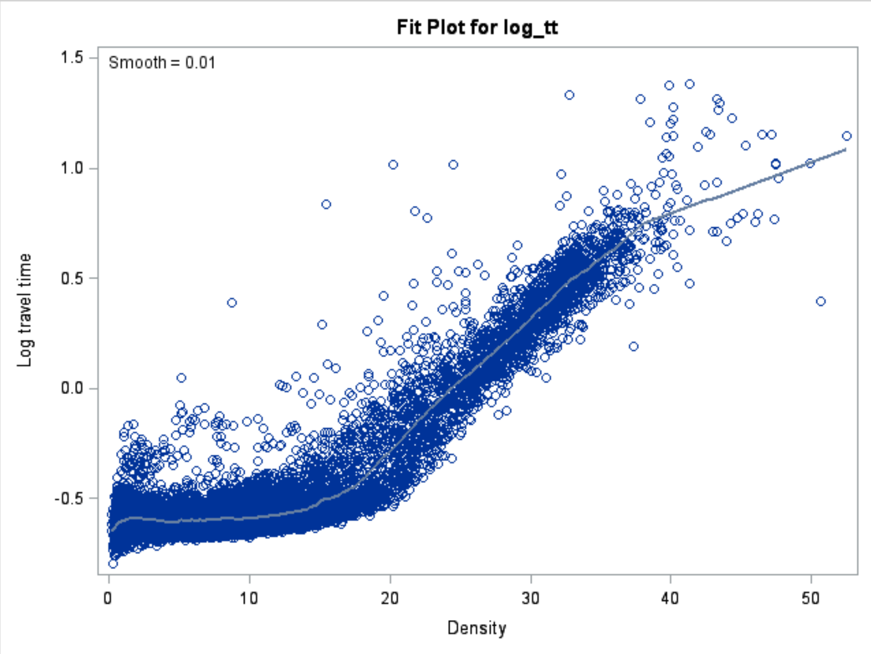
where $X_{i,j}$ is the weather variable j observed at time i and β_j are the corresponding estimation coefficients. α is the constant term and ϵ_i is a stochastic error term.

The main reason for the two step procedure is that we have no use for a parametric description of the speed flow curve. We are mainly interested in the effect from the weather. In addition, we avoid systematic residuals stemming from a concrete parametric specification. As mentioned, the traffic data and the weather variables are only slightly correlated and this justifies the split into two steps. In step 1 we omit all weather variables and in step 2 we omit the density variable, but that would only lead to biased estimates if density is correlated with the weather variables and that is generally not the case. One exception could be darkness whish has a correlation coefficient with density of -0.22.

When speed is modelled as a function of flow, a problem of endogeneity arises in hypercongestion conditions since it is not only the flow that determines speed, but the low speed will reduce the flow as well. Thus, it is not clear whether we are estimating the speed-flow curve or the motorists' behaviour such as route choice or time of departure. The same problem is present when estimating travel time as a function of density as done here. High travel times in hypercongestion will in turn result in lower density due to lower inflow to the road. As long as we are estimating the relationship non-parametrically, the problem does not yield biased parameter estimates and since we are mainly interested in how the weather shifts the curve, the problem is of minor importance. However, the problem means that the presented weather effects are conditional on the density and we thus disregard that the weather may change the density in hypercongestion.

Step 1

In step 1 log(travel time) is estimated non-parametrically against density using the SAS Loess procedure with a smoothing parameter of 0.01 which means that each point is estimated using 1% of the observations closest to the evaluation point along the density axis. For segment 1 the observations and the fitted curve looks like this:



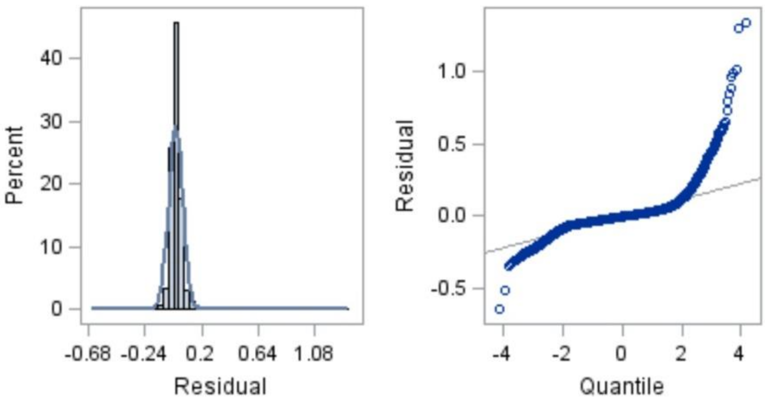
The kink to the right cannot be trusted because of very few observations with high density. Common for the three segments is that the maximum capacity occurs at a density of around 20 cars per km which corresponds to a maximum flow of 27-30 cars per minute and speeds around 90 km/h. The exact numbers are shown in the table below.

Estimated maximum flow

Fitted curve	Maximum flow (capacity)	Speed at max. flow	Density at max. flow
Segment	Cars per minute	km/h	cars per km
1	27.4	92.0	17.9
2	29.1	86.9	20.1
3	30.2	85.2	21.3

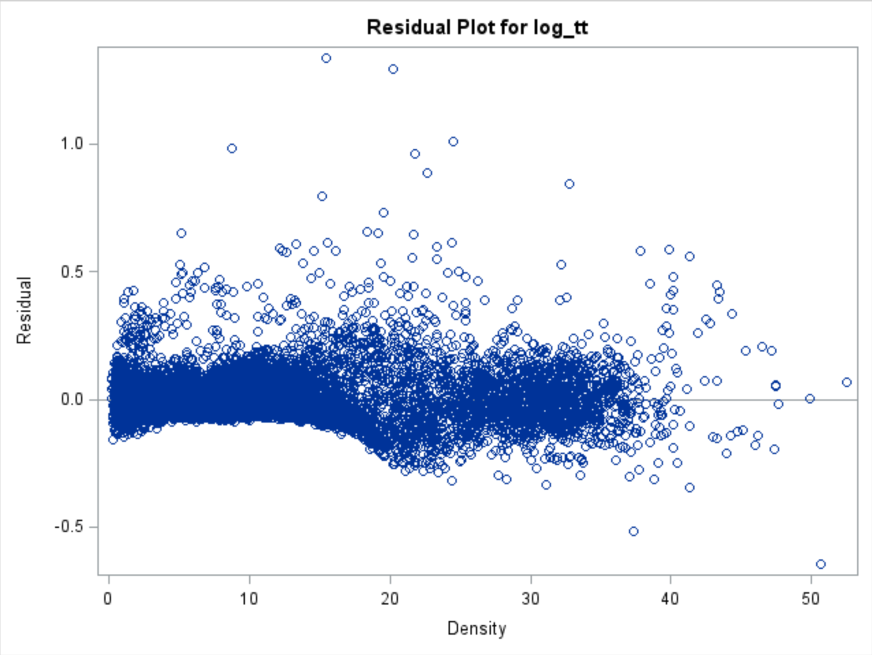
Note: the numbers are per lane.

It is clear from the fit plot graph above that there are some very high positive residuals, but only few with very high negative residuals. In spite of this, thanks to the high number of observations, the distribution of the residuals looks close to normal, but with longer tails – see the graphs below. The SAS Loess procedure is in principle able to compute confidence intervals around the estimated curve, but fails – probably because of the high number of observations.



Step 2

In step two the residuals from above are used as explanatory variable and estimated linearly against the weather variables. The residuals from step 1 can be seen in the graph below.



The estimations are spit into density intervals to reveal potential differences. The intervals chosen here are: 0-3, 3-6, 6-10, 10-20, 20-30 and above 30 (cars per km).

The first estimation trials included the continuous weather variables directly and many turned out to yield good results for low-medium densities, but through trial and error the weather variables have subsequently been categorized to simple dummy variables which also perform well. At this point the dummies applied are:

Darkness:	yes/no. Darkness is here excluding civil twilight periods
Frost:	yes/no. Frost at ground level
Snow:	yes/no. Snow on the ground measured in the morning
Light precipitation:	yes/no. Positive up to 2mm per hour
Heavy precipitation:	yes/no. Above 2mm per hour
Haze:	yes/no. Visibility between 1000 and 10,000m
Fog:	yes/no. Visibility below 1000m
Wind:	yes/no. Mean wind above 5m/s

The expected sign for the coefficients for these dummies are all positive. In the table below, the estimation results for segments 1, 2, and 3 are shown.

Log travel time residuals estimation, segment 1

Density	0-3	3-6	6-10	10-20	20-30	above 30
No. obs.	5390	7163	16899	8229	1223	885
RMSE	0.0459	0.0372	0.0338	0.0650	0.1449	0.1225
R^2	0.1115	0.0548	0.0412	0.0442	0.0553	0.0534
Intercept	**-0.0197**	**-0.0075**	**-0.0025**	**-0.0051**	-0.0039	-0.0079
Darkness	**0.0082**	**0.0025**	0.0012	**-0.0101**	**-0.0523**	0.0200
Frost	**0.0107**	**0.0086**	**0.0047**	-0.0004	0.0168	-0.0155
Snow	**0.0264**	**0.0109**	**-0.0054**	**0.0320**	**0.0882**	**0.1007**
Light prec.	**0.0246**	**0.0270**	**0.0300**	**0.0498**	**0.0676**	0.0346
Heavy prec.	**0.0352**	**0.0340**	**0.0453**	**0.0718**	0.0311	-0.0447
Haze	**0.0170**	**0.0103**	**0.0049**	**0.0088**	0.0136	0.0033
Fog	**0.0080**	**0.0086**	**0.0264**	-0.0029	0.0122	0.0019
Wind	**0.0077**	**0.0038**	0.0006	0.0009	0.0187	-0.0029

Bold numbers are significant at 1% level

Log travel time residuals estimation, segment 2

Density	0-3	3-6	6-10	10-20	20-30	above 30
No. obs.	3450	4376	10854	3538	903	494
RMSE	0.0401	0.0315	0.0351	0.0649	0.1188	0.1018
R^2	0.1298	0.1854	0.0984	0.048	0.0768	0.1613
Intercept	**-0.0207**	**-0.0142**	**-0.0080**	**-0.0077**	**-0.0291**	**-0.0310**
Darkness	**0.0120**	**0.0106**	**0.0096**	-0.0011	-0.0025	**0.0537**
Frost	**0.0077**	**0.0094**	**0.0075**	**0.0143**	**0.0453**	0.0346
Snow	**0.0090**	**0.0121**	**0.0106**	**0.0195**	**0.0419**	0.0356
Light prec.	**0.0315**	**0.0292**	**0.0294**	**0.0488**	0.0700	**0.0762**
Heavy prec.	**0.0781**	**0.0455**	**0.0624**	**0.0813**	0.0417	-0.0716
Haze	**0.0158**	**0.0161**	**0.0141**	0.0028	0.0132	0.0173
Fog	**0.0111**	**0.0222**	0.0099	-0.0091	-0.0052	0.0145
Wind	**0.0099**	**0.0046**	**0.0027**	0.0029	**0.0311**	-0.0037

Bold numbers are significant at 1% level

Log travel time residuals estimation, segment 3

Density	0-3	3-6	6-10	10-20	20-30	above 30
No. obs.	2893	3711	9095	4199	1460	22
RMSE	0.0626	0.0375	0.0404	0.0733	0.1143	0.3645
R^2	0.0247	0.1203	0.0481	0.047	0.1127	0.1386
Intercept	**-0.0067**	**-0.0124**	**-0.0041**	**-0.0060**	**-0.0276**	0.1600
Darkness	0.0041	**0.0099**	**0.0173**	0.0050	**0.0343**	-0.2357
Frost	0.0020	**0.0101**	**0.0068**	-0.0034	-0.0076	no obs.
Snow	**0.0159**	**0.0203**	**0.0127**	**0.0459**	**0.0960**	no obs.
Light prec.	**0.0205**	**0.0142**	**0.0111**	**0.0322**	**0.0897**	-0.3288
Heavy prec.	**0.0628**	**0.0284**	**0.0352**	**0.0616**	0.0245	no obs.
Haze	0.0053	**0.0089**	**0.0041**	0.0028	**0.0256**	no obs.
Fog	-0.0091	**0.0165**	**0.0176**	-0.0194	-0.0136	-0.4800
Wind	-0.0041	0.0001	-0.0016	-0.0024	-0.0046	-0.1410

Bold numbers are significant at 1% level

The main impression from the three segments is that most of the weather variables have a negative impact on the speed when the density is low. When density is medium and especially high the impact is more dubious. In most instances the effect is of the expected sign. Precipitation and especially snow seem consistently to have effect at low and medium densities. These two variables also in general have the largest effect. In most instances heavy precipitation is – as expected – estimated to have larger effect than light precipitation. The parameters can be interpreted as relative travel time changes when the indicated weather condition is present compared to when it is not. Thus, precipitation increases travel time (or decreases speed) by 3-6% or even more compared to dry conditions. The effect from darkness, frost, wind and fog/haze seem to be less and they are to a larger extent confined to low densities (less than 10 cars per km). Surprisingly, there is no clear tendency that fog reduces speed more than haze.

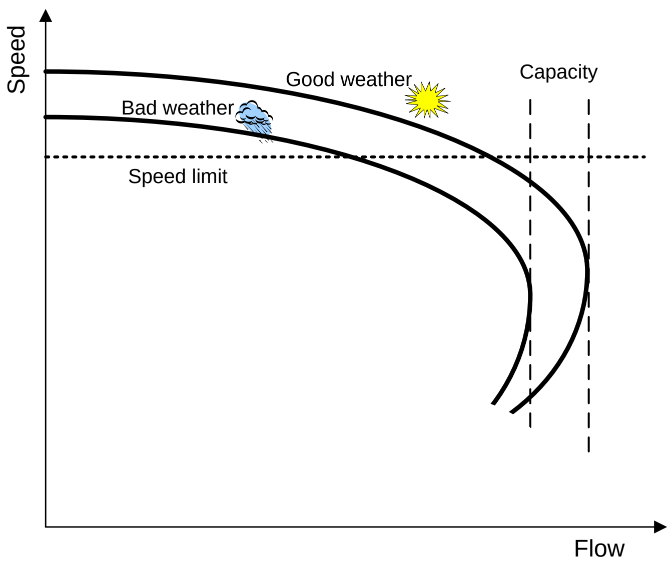
Furthermore, there is a clear tendency that the standard deviation of travel time starts to increase when the density exceeds 10 and even more when it is over 20 – i.e. when there is hypercongestion. Congestion clearly has an extra cost apart from higher expected travel time – there is also a cost attached to unpredictable travel time. When the density is extremely low, the standard deviation increases a bit as well. But this may stem from drivers who are tempted by the empty roads to exceed the speed limit. This is supported by the observations that the average speed is relatively high when density is close to zero. But these considerations are not related to the weather variables.

The issue of endogeneity naturally comes up here. The estimated effects from weather are probably valid when density is below approximately 20 because an increase in density does not affect the speed. If it is above 20, the weather effect may be hidden in the results above because density is kept fixed. Therefore it has been tested if estimation of the travel time as function of the flow combined with weather data when density is higher than 20 may yield better results. This is described in section B which deals with estimation of the speed-flow curve in two phases.

Some few combinations of the dummy variables have been tried as well, but they are in general not significant. Darkness and precipitation have been combined (multiplied together) from the assumption that reflections in a wet windshield or a wet road disturb the visibility. Frost and precipitation have been combined as well as attempt to construct a proxy for snowfall. As mentioned, the results could not confirm that these variables have effect as long as the non-combined variables are included.

A simple one-step linear estimation procedure has been tested as well. Here, log travel time is estimated linearly directly on the weather variables for the same density intervals as above and the density is included as an extra explanatory variable. The results are not far from the ones presented above.

The fact that the segments are covered by a speed limit of 110 km/h could mean that the speed, when the flow is small, is generally lower than the road conditions allow for. Therefore, one could a priori expect that when the flow is low, bad weather will not affect the speed since the speed is already kept down artificially. See the figure below.



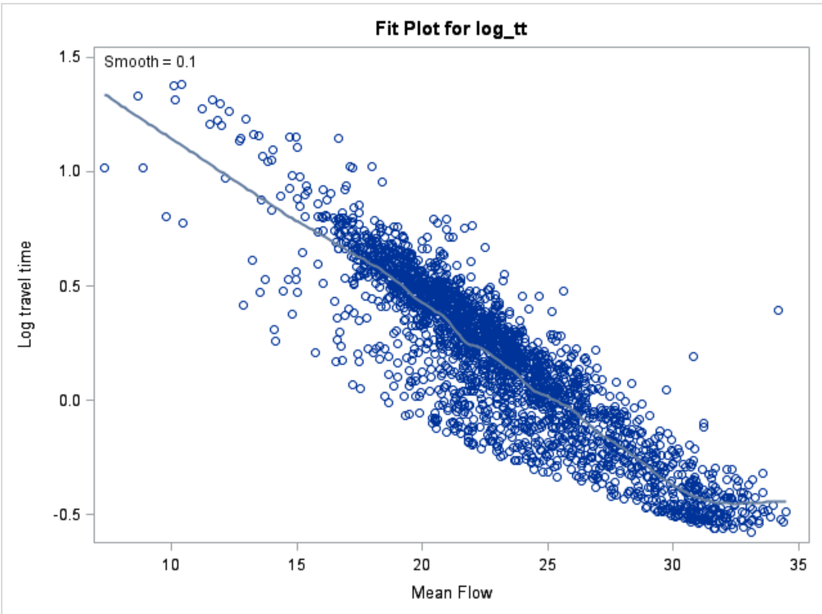
The results from the estimations do only partly confirm this hypothesis. There is a weak tendency that the coefficients for rain and snow do go up as the density (and thus the flow) increases from low to medium, but at the same time the standard deviation of the parameters increase, making the conclusion weak. It would be interesting to carry out analyses on roads with no speed limit to see if this will change the pattern, but data for such roads do not exist for Denmark. There are some roads with a 130-km/h speed limit and they might be worth analyzing for comparison.

Around 10% of the observations have weather data which are interpolated (over time) or borrowed from a neighbouring station (e.g. Copenhagen Airport). To check if this has implications for the results, the estimations are repeated without these observations. This means reducing the number of observations from 39.789 to 36.48 for segment 1, from 23.615 to 20.964 for segment 2, and from 21.380 to 18.939 for segment 3. We get much the same results as above: The coefficients have the same order of magnitude and the same coefficients are significant. But it seems to imply slightly lower coefficients for snow and slightly higher for precipitation. The small changes indicate that the data repair hasn't harmed the analysis.

B. Test with estimations on the speed-flow curve divided into two phases

As mentioned above, there may be a benefit from estimating the speed-flow curve with the observations divided into two phases: hypercongested and non-hypercongested. Again, a two step procedure is chosen: 1) log(travel time) is estimated non-parametric against flow. 2) The residuals from the first estimation are estimated linearly against the weather variables as before. We now estimate the weather effect conditional on the flow as opposed to the results presented above which were conditioned on the density.

The splitting of the observations is based on the density at maximum flow derived from the step 1 estimations using density above. Because of few observations from hypercongestion conditions, a larger smooth parameter of 0.1 is chosen. In hypercongested conditions we get the following result for segment 1 from step 1:



Results from step 2 from the three segments are found in the following table.

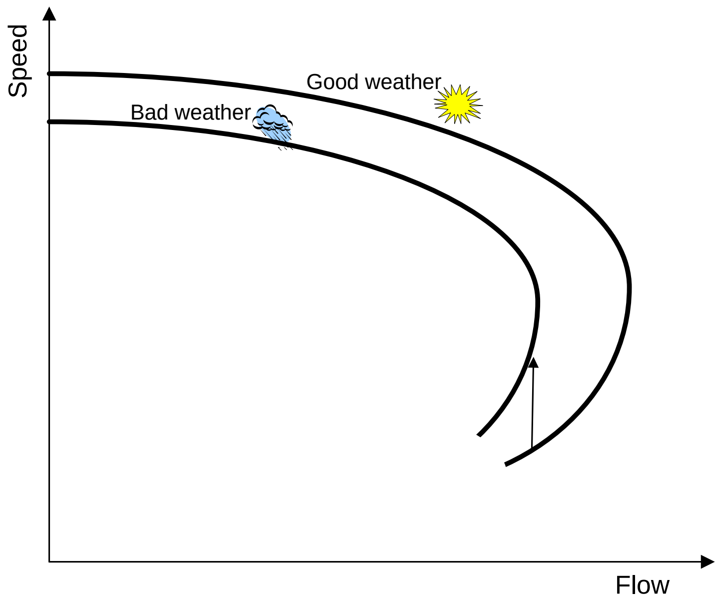
Log travel time residuals estimation using flow as independent variable

Conditions	Free-flow and moderate congestion			Hypercongestion		
Segment	1	2	3	1	2	3
Density	below 17.9	below 20.1	below 21.3	above 17.9	above 20.1	above 21.3
No. obs.	37384	22234	20127	2405	1381	1253
RMSE	0.0454	0.0457	0.0590	0.1587	0.1516	0.0763
R^2	0.0411	0.0760	0.0363	0.0155	0.0538	0.0427
Intercept	**-0.0060**	**-0.0109**	**-0.0061**	0.0063	0.0135	**0.0125**
Darkness	**0.0022**	**0.0066**	**0.0029**	0.0086	**-0.0356**	**-0.0216**
Frost	**0.0071**	**0.0090**	**0.0072**	-0.0042	**-0.0759**	-0.0149
Snow	**0.0082**	**0.0121**	**0.0219**	**-0.0642**	0.0276	-0.0072
Light prec.	**0.0334**	**0.0329**	**0.0181**	-0.0422	-0.0358	0.0044
Heavy prec.	**0.0523**	**0.0667**	**0.0453**	-0.0158	-0.0555	0.0445
Haze	**0.0100**	**0.0135**	**0.0068**	0.0066	**0.0334**	0.0038
Fog	**0.0110**	**0.0089**	-0.0011	-0.0025	0.0083	0.0050
Wind	**0.0017**	**0.0049**	-0.0013	-0.0176	-0.0066	**-0.0194**

Bold numbers are significant at 1% level

The results from non-hypercongestion conditions confirm the results from above: Most weather variables have effect on speed; in particular precipitation and the size of the effects in general match the former findings.

In hypercongestion mode most coefficients have the opposite sign than was the case before with only one exception, but most coefficients are insignificant. Apparently, the weather effect is weak in hypercongestion. Perhaps traffic is already constrained by the large density so that bad weather does not reduce speed any further. The negative signs of the coefficients have a good explanation: for a given flow the speed will go up when traffic is moving from good to bad weather conditions as long as traffic is hypercongested – see the figure below. This is not in conflict with the positive signs when estimating conditional on density. Thus, in hypercongestion conditions there are indications of weather effects as expected, but they are slight.



The figure also points at a problem when estimating conditional on flow close to the capacity: We will have very few observations with bad weather here because the weather has reduced the road capacity. Thus, it hardly makes sense to estimate weather effect on the speed-flow curve when the flow is high. This is an argument in favour of the estimation against density as in section A. The next section (C) deals with the effect from weather on the capacity.

C. Effect on capacity

As a supplement to the estimations in section A, the weather effect has been estimated in the neighbourhood of the density at the maximum flow in order to assess the weather effect on the capacity. Thus, for segment 1 the estimation is based on the density interval 15-21, for segment 2: 17-23, and segment: 3 18-24. As before, we estimate log(travel time) none-parametric against density in step 1 and estimate the residuals linearly against the weather variables in step 2. The change in capacity is calculated as the difference in the maximal predicted flow from step 1 with and without the presence of each weather dummy variable. Capacity is found as:

$$Cap = \max_{\mathrm{i}}\{\text{Predicted flow}_{\mathrm{i}}\} \quad \text{where}$$

$$\text{Predicted flow}_{\mathrm{i}} = \frac{\text{density}_{\mathrm{i}}}{\exp(\text{predicted}\log(\text{travel time}_{\mathrm{i}}))}$$

Here, i is an index of the observations. The results are shown in the table below.

Log travel time estimation at max capacity

Segment	1		2		3	
Density	15-21	17.9	17-23	20.1	18-24	21.3
No. obs.	1098	Change in capacity, cars/minute	551	Change in capacity, cars/minute	1083	Change in capacity, cars/minute
RMSE	0.1422		0.1315		0.1308	
R^2	0.0918		0.0745		0.0610	
Intercept	-0.0016	0.0	-0.0098	0.3	-0.0206	0.6
Darkness	**-0.0747**	2.1	**-0.0617**	1.9	0.0063	-0.2
Frost	0.0242	-0.7	0.0262	-0.8	0.0045	-0.1
Snow	**0.0773**	-2.0	**0.0753**	-2.1	**0.0693**	-2.0
Light prec.	**0.1054**	-2.7	0.0514	-1.5	0.0749	-2.2
Heavy prec.	**0.2202**	-5.4	0.0176	-0.5	0.0261	-0.8
Haze	0.0167	-0.5	0.0058	-0.2	0.0232	-0.7
Fog	0.0006	0.0	-0.0180	0.5	-0.0570	1.8
Wind	**0.0245**	-0.7	**0.0274**	-0.8	-0.0008	0.0

Bold numbers are significant at 1% level

There are only few significant speed changes with the expected sign. Snow is the only variable that is significant and consistently decreasing capacity by around 2 cars per minute. Since the maximum flow lies around 27-30 cars per minute, this means a percent capacity reduction of 7-8% (which is also the value of the estimated parameter). Precipitation seems to reduce capacity in the same order of magnitude (though very high for segment 1), but often the speed reduction is not significant. Darkness seems for some reason to increase capacity for segment 1 and 2, but this may be due to the correlation between density and darkness. Also a bit surprising: wind has a small reducing effect on capacity for segment 1 and 2.

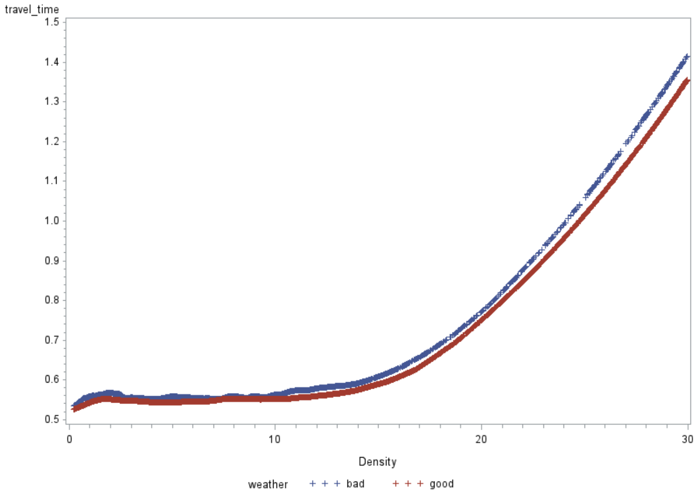
Here, the only safe conclusion is that snow on the ground consistently reduces capacity by around 7-8%. It should be said though that this result covers snow on the ground observed at a station around 15 km from the road and the conditions on the road may be different. Often a thin snow cover is quickly removed by the traffic, so the estimated effect may cover thicker layers of snow. Precipitation probably has a similar effect as snow, but the size is difficult to determine.

D. Good weather – bad weather

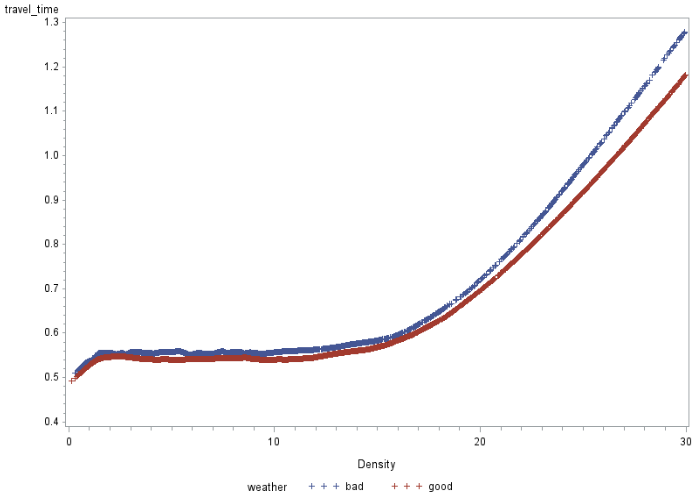
The estimations above indicate that snow and precipitation consistently reduces speed. Also frost and fog seems to have an effect. Therefore the observations are split into two sets, one with bad weather defined as observations with one or more of the following properties: precipitation above zero, snow depth above zero, frost at ground level, or visibility below 1000m. The rest of the observations are characterized as good weather. The proportion of bad weather is 18%, 26%, and 24% for the segments 1, 2, and 3.

For each segment, the non-parametric estimation of log(travel time) against density is repeated with the two sets separately. Now, a smoothing parameter of 0.05 is used to get smoother curves. In the figures below log(travel time) is converted to travel time (minutes per km). The figures are cut off at density 30.

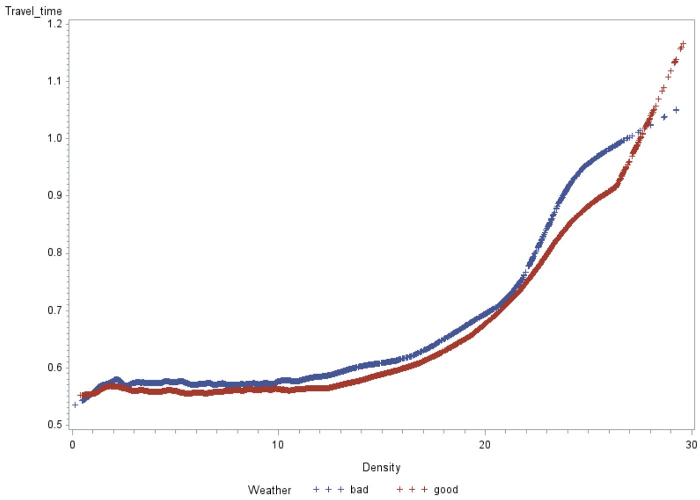
Travel time vs. density
in good and bad weather, segment 1



Travel time vs. density
in good and bad weather, segment 2



Travel time vs. density
in good and bad weather, segment 3



The fitted lines make it possible to assess roughly the reduction in capacity going from good to bad weather by calculating the maximum predicted flow along the fitted curves. This is done in the table below.

Maximum flow (cars/min.)

	Good weather	Bad Weather	Change	%-change
Segment 1	26.92	26.12	-0.80	-3.0%
Segment 2	28.78	27.94	-0.84	-2.9%
Segment 3	29.64	29.39	-0.25	-0.8%

There seems to be an effect of reduced capacity in bad weather. This confirms the capacity reductions found above, but here the effects are lower, probably due to the mixing of variables defining "bad weather". For segment 3 the decrease is small, and this is due to the downward bulge on the bad weather curve at the density around 22, which is close to the maximum flow density. This could be a coincidence.

E. Travel time variability

Apart from the travel time, also travel time variability may be influenced by the weather. To explore the effect from weather on travel time variability, the two-step estimation of the travel time-density curves (section A) are repeated, but in step 2 the residuals from step 1 are now replaced by the squared residuals from step 1. In this way it is possible to assess how the individual weather variables affect travel time variability. The results are shown in the table below.

Log travel time squared residuals estimation, segment 1

Density	0-3	3-6	6-10	10-20	20-30	above 30
No. obs.	5390	7163	16899	8229	1223	885
RMSE	0.0086	0.0103	0.0096	0.0281	0.0739	0.0425
R^2	0.0772	0.0084	0.0168	0.0034	0.0038	0.0075
Intercept	0.0000	**0.0010**	**0.0007**	**0.0042**	**0.0256**	**0.0196**
Darkness	0.0003	-0.0007	-0.0002	0.0024	-0.0045	0.0016
Frost	**0.0020**	**0.0019**	**0.0035**	-0.0008	-0.0020	-0.0016
Snow	**0.0049**	0.0005	**-0.0024**	0.0039	0.0072	0.0007
Light prec.	-0.0001	0.0016	0.0008	0.0027	0.0059	-0.0030
Heavy prec.	0.0004	0.0009	**0.0031**	0.0057	-0.0092	-0.0070
Haze	**0.0026**	**0.0013**	**0.0007**	0.0007	-0.0058	-0.0055
Fog	0.0008	**0.0022**	**0.0094**	0.0022	-0.0124	-0.0102
Wind	**0.0009**	0.0003	0.0002	-0.0012	0.0006	-0.0041

Bold numbers are significant at 1% level

Log travel time squared residuals estimation, segment 2

Density	0-3	3-6	6-10	10-20	20-30	above 30
No. obs.	3450	4376	10854	3538	903	494
RMSE	0.0058	0.0046	0.0184	0.0372	0.0667	0.0318
R^2	0.0704	0.0373	0.0017	0.0009	0.0146	0.0270
Intercept	**0.0006**	**0.0005**	**0.0013**	**0.0042**	**0.0133**	**0.0158**
Darkness	**-0.0005**	0.0002	0.0000	-0.0023	-0.0064	0.0041
Frost	**0.0010**	-0.0001	-0.0003	0.0022	-0.0023	-0.0002
Snow	**0.0016**	**0.0010**	0.0006	-0.0013	0.0013	0.0055
Light prec.	**0.0021**	0.0008	0.0011	0.0002	-0.0042	0.0046
Heavy prec.	**0.0093**	**0.0031**	**0.0066**	0.0046	-0.0078	-0.0129
Haze	**0.0020**	**0.0012**	0.0009	-0.0003	-0.0034	**-0.0089**
Fog	0.0003	**0.0038**	-0.0006	-0.0017	0.0029	-0.0123
Wind	**0.0011**	**0.0004**	-0.0003	0.0009	**0.0159**	-0.0061

Bold numbers are significant at 1% level

Log travel time squared residuals estimation, segment 3

Density	0-3	3-6	6-10	10-20	20-30	above 30
No. obs.	2893	3711	9095	4199	1460	22
RMSE	0.0861	0.0063	0.0227	0.0675	0.0456	0.2125
R^2	0.0020	0.0394	0.0008	0.0003	0.0041	0.1152
Intercept	**0.0101**	**0.0006**	0.0010	**0.0060**	**0.0168**	**0.1822**
Darkness	-0.0064	0.0001	0.0010	-0.0032	-0.0043	-0.1764
Frost	-0.0028	0.0005	0.0004	0.0007	-0.0040	no obs.
Snow	0.0009	**0.0020**	0.0007	0.0006	0.0050	no obs.
Light prec.	-0.0016	-0.0006	-0.0002	-0.0033	0.0011	-0.1537
Heavy prec.	0.0037	-0.0004	0.0005	-0.0003	-0.0119	no obs.
Haze	-0.0033	**0.0011**	0.0004	-0.0006	-0.0005	no obs.
Fog	-0.0047	**0.0060**	0.0049	-0.0015	-0.0072	-0.0798
Wind	-0.0007	**0.0008**	0.0009	0.0006	-0.0017	-0.1145

Bold numbers are significant at 1% level

There is a clear tendency that variability is affected by the weather as long as density is low (below 5 or 10 cars per km) and, as expected, in most instances bad weather increases travel time variability. But there is no clear pattern that some weather variables are more important and others not, and many of the coefficients are not significant. For segment three the effects even seem almost absent. From these estimations we cannot conclude much about the size of the effects, but they give an indication that there may be a weather effect in travel time variability.

Conclusions

The estimations confirm that bad weather reduces travel speed on the highway, but primarily when there is no hypercongestion. In addition, the capacity of the roads seems to be reduced. Precipitation and snow on the ground have the strongest effect, but the effects seem to be smaller than found in other studies. Precipitation reduces speed by 3-6% or a little more (heavy rain more than light rain) and snow on the ground by 1-2%, but there is a weak tendency to higher effects close to capacity i.e. when density is close to 20 cars per minute. Capacity is reduced by around 7-8% with snow on the ground and probably something in the same order of magnitude when there is precipitation. The data indicates that also travel time variability goes up in bad weather, but this conclusion is weaker.

The non-parametric approach to the speed-flow or travel time-density curves has proven to be fruitful and makes it possible to analyse weather effects without the constricting ties from a specific parameterization of the curves.

The analyses would benefit from better data. Some of the more rare weather events such as storm and snow are poorly represented in the data especially when density is high and more data could improve conclusions on these rare combinations. Weather observations closer to the highway could most likely improve the reliability of the findings. The same goes for snow observations with higher frequency than the daily available here. In addition, there is a need for data on the precipitation type. The problems of proximity and precipitation type could maybe be overcome by radar data that are continuously published with 10 minutes frequency and with a quite high spatial resolution. The traffic data could be improved as well. Inclusion of information on the share of heavy (long) vehicles and better information on road incidents would improve the analyses.

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