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Mohammad Sabir[1]
Mark Koetse[1]
Jos Van Ommeren[1,2]
Piet Rietveld[1,2]

[1] Dept. of Spatial Economics, Faculty of Economics and Business Administration, VU University Amsterdam;
[2] Tinbergen Institute.

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Tinbergen Institute Amsterdam
Roetersstraat 31
1018 WB Amsterdam
The Netherlands
Tel.: +31(0)20 551 3500
Fax: +31(0)20 551 3555

Tinbergen Institute Rotterdam
Burg. Oudlaan 50
3062 PA Rotterdam
The Netherlands
Tel.: +31(0)10 408 8900
Fax: +31(0)10 408 9031

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Muhammad Sabir*[,1], Mark Koetse[1], Jos Van Ommeren[1,2] and Piet Rietveld[1,2]

[1] Department of Spatial Economics, VU University Amsterdam, The Netherlands

[2] Tinbergen Institute, Amsterdam, The Netherlands

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* Corresponding author: VU University Amsterdam, Department of Spatial Economics, De Boelelaan 1105, 1081 HV, Amsterdam, The Netherlands. Email: msabir@feweb.vu.nl

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Abstract

In the present study we carry out an analysis of speed fluctuations as a determinant of the quality of public transport. We do this by focusing on a special cause of unreliability: variations in weather conditions. We use hourly measured weather conditions. The panel data results imply that snow has a substantial negative effect on the speed public transport. The associated welfare loss is 53 eurocent per commuting trip per person made by train and 76 eurocent per commuting trip per person made by bus, tram and metro. Rain strongly affects the speed of bus, tram and metro commuting trips on congested routes. The associated welfare loss is 1.15 € per commuting trip per person.

Introduction

The main modes of transportation in the Netherlands are car, bicycle and walking. They cover about 90 percent of all trips. About 50 percent of trips are made by car, and the main alternative for the car is the bicycle, with a share of about 25 percent. Distance appears to be an important moderator, as people prefer to not use the bicycle for longer distances. Three-quarters of all bicycle journeys to work is less than 5 kilometres, one fifth is between 5 and 10 kilometres, and 5 percent is longer than 10 kilometres (Statistics Netherlands 2008). Longer commuting trips are mostly made either by car or by public transportation. Since using the car is not always a viable option, e.g., because no drivers license is available or because of parking restrictions (especially in the Randstad region[1]), public transport in the Netherlands is frequently a good alternative for trips over longer distances. Public transport will be classified in two main categories, i.e., trips made by bus, tram and metro on the one hand, and trips made by train on the other.[2]

Public transport in the Netherlands has about an 8 percent share of trips. When travelling by public transport, an individual has to go to an access point (bus stop, train station, etc.). The more time is spent getting to an access point, the larger the total time required to reach the final destination. Transferring between trains or buses during a trip has a similar effect. Furthermore, waiting time, delays and adverse weather may also influence the speed of a trip and hence total travel time. Thus, the need for and importance of integrating the different segments of the journey is clear.

Compared to car trips, the speed of public transport is often a weak element of multimodal transport chains. In the large majority of the cases car trips are considerably faster than public transport trips, and it is therefore not surprising that the modal share of the car is much higher than that of public transport. There are two exceptions to his, leading to market segments where public transport tends to perform relatively well: in congested areas and for long distance trips where the high speed of trains is a large advantage. The first sub market is an example that push factors (congestion on the road, parking problems in cities) are an important factor contributing to the success of public transport. In all cases it is clear that a key success factor for integrated public transport is that it achieves speeds that are competitive to those offered by car transport.

A related consideration is that reliability of transport services is an important determinant of the quality of multimodal trips: when delays occur in part of a trip, travellers may miss their connection, leading to extra waiting time at transfer points and possibly high scheduling costs. Thus variations in speed in a certain part of a trip chain may lead to substantial extra waiting or travel time in the rest of the trip.

The potential success of integrated transport therefore depends considerably on the degree of its reliability. To make integrated public transport successful it is therefore important that transport organisations can cope with these uncertainties in an adequate way, i.e., such that the effects for the travellers are minimised. Elements of such policies are that time tables are made in such a way that there is some slack at transfer points. This may make the average speed slightly slower, but it would reduce the negative impact of disturbances (Rietveld *et al.* 2001). Another element would be a high level of integration between services at the operational level, for example, the bus driver waits a few minutes when it is known that the train is some minutes late.

This underlines the importance of various 'soft' dimensions to achieve integrated public transport of high quality. One is the dimension of human resource management: drivers should be motivated to serve passengers properly. Time tables should be obeyed where possible, but in case of disturbances flexibility is needed. Another important aspect of integrated public transport is the institutional dimension: when one integrated company is responsible for the overall quality of a multimodal chain this creates favourable conditions for high quality, reliability and flexibility. On the other hand, with one integrated (bus-rail) company the potential benefits of competition may be lost. This leads to challenging questions of how to combine the better elements of both worlds.

In the present study we carry out an analysis of speed fluctuations as a determinant of the quality of public transport. We do this by focusing on a special cause of unreliability: variations in weather conditions. We find that this is a relatively underexplored theme of research. We will focus on commuting trips. This is an important part of the trips made by public transport. The advantage of focusing on commuting is that weather variations will most probably not affect the decision of travellers to stay at home, which might lead to selectivity effects. This makes it easier to analyse commuting trips compared with for example recreational trips. Please note that by travel time of a trip we mean travel time of a complete door to door trip, i.e., it not only includes the in-vehicle time but also includes time spent on access and/or egress modes, waiting times and delays.

During the past decades comparatively little attention has been paid to the effects of weather on transportation in general, and on public transport in particular. An overview of the empirical literature on weather and transport can be found in Koetse and Rietveld (2009). Most of the available empirical studies on weather and transport report a reduction in speed during adverse weather conditions (see e.g., Martin *et al.* 2000; Hranac *et al.* 2006; Maze *et al.* 2006). The major reduction in speed of road transport is due to precipitation and snow. Martin *et al.* (2000) report a 10 percent speed reduction in wet conditions and a 25 percent reduction in slushy and wet conditions. These results are confirmed by Hranac *et al.* (2006) using detailed traffic and weather data from 2002 to 2004 for the Baltimore, Seattle and Minneapolis-St. Paul metropolitan areas. They find that light rain reduces the free flow speed by 3 percent and the speed at full capacity by 9 percent. Reduction in speed increases with rain intensity, with maximum reductions of around 6-9 percent for free flow speed and 8-14 for speed at capacity (see also Ibrahim and Hall 1994; Hall and Barrow 1988; Maze *et al.* 2006). Finally, Sabir *et al.* (2008) report negative but small effects of adverse weather on the speed of car commuter trips. However, the effect of snow is substantial, with speed reductions of around 7 percent. Furthermore, although the effects of rain on speed are small in general, rain causes a speed reduction of 10-15 percent for trips made during rush hours on congested routes.

Interestingly, these studies mainly focus on road transport (but see Hranac *et al.* 2006, for an exception). Public transport is largely ignored. Whereas trip speed reductions for car transport are mainly caused by congestion, public transport delays are also and perhaps mainly caused by technical failures. Therefore, the current study contributes to the limited available empirical evidence by providing a closer insight into the effects of weather conditions on the speed of public transport commuting trips and the welfare affects associated with the changes in travel time.

The rest of the paper is organized as follows. Section 2 discusses the data as well as the descriptive statistics of the variables. Section 3 explains the econometric methodology used to analyse the effects of weather and individual characteristics on the speed of commuting trips made by public transport. Section 3 also discusses the explanatory variables included in the model. Section 4 provides the empirical results and discusses the welfare effects of weather conditions for the Netherlands. Section 5 concludes.

1. Data

The data used in this paper are taken from two main sources. We make use of a transportation survey (MON) for the years 2004 and 2005. The MON transportation survey contains information about 130,000 persons who reported the trips they made on one particular day during these two years, leading to about 450,000 reported trips.[3] The data also contain information about important individual and household characteristics. The second data source is a weather database of the Royal Netherlands Meteorological Institute (KNMI) for the years 2004 and 2005. It contains weather conditions on an hourly basis by 32 weather stations spread over the entire Netherlands. We use the weather conditions from the weather stations which are nearest to places of departure (in almost all cases). The average distance to a weather station is about 12 to 13 km, which means that our measurement of weather conditions is fairly local.[4] The weather conditions refer to temperature, wind speed, visibility, rain and snow. By combining these two data sources we are able to analyse for each trip the local weather conditions of the hour in which the trip took place.

We select only commuting trips for a number of economic and statistical reasons. First, because the demand for commuting is derived from the demand for workers, which does not directly depend on weather, whereas the derived demand for other trips (in particular, leisure trips) are affected by weather conditions. Hence, for commuting trips, the interpretation of the welfare effect of weather is more straightforward. Second, commuters are a relatively homogeneous group of travellers for which assumptions on the value of time are likely to be more accurate. Third, we select public transport trips because for other trips, in particular bicycle trips, the welfare of commuting is directly affected by weather, e.g., it is unpleasant to take the bicycle on a rainy day because one gets wet, and not so much because of reductions in speed. Fourth, the selection of a sample may generate biased estimates of the coefficients of variables (Wooldridge 2003). Fifth, adverse weather may increase the risk of travel speed for car use due to accidents, but this is less likely for public transport users. Finally, commuters generally take at least two trips per day, panel estimation techniques can be employed to deal with this issue.

Given these selections, our sample contains 13,618 public transport trips made by 2,225 commuters. Average trip distance is 32.9 km, average trip speed is 31.7 km/hour, and average travel time per trip is 57.5 minutes. The descriptive statistics for bus, tram and metro, and train are given along with other explanatory variables in Appendix A.

It is important to realize that the speed as we measure it is based on the travel time of the *whole* trip rather than only in-vehicle travel time. This implies that this travel time also includes the time to reach to access point, waiting time, in-vehicle time, and time to get to the final destination from the arrival. The average in-vehicle travel time for public transport is 24.6 minutes. Average in-vehicle travel time for bus/tram/metro is 21.6 minutes. Whereas, average in-vehicle travel time for train is 30 minutes. It appears that the share of in-vehicle time in the total trip time of bus/tram/metro trips and train trips is about 50 percent and 45 percent, respectively. This implies that public transport travellers spend a significant part of their total travel time on access/aggress modes or on waiting time. Additionally, this also explains why the average speed of public transport trips is low.

2. Model specification and estimation procedure

Similar to Sabir *et al.* (2008) the interpretation of our empirical analysis is based on standard micro-economic theory such as used in Van Ommeren and Dargay (2006), who derived a structural model for commuting speed and then used that model for Great Britain, as well as Fosgerau (2005) who applied it to Denmark.[5]

Van Ommeren and Dargay (2006) assume that commuters optimally chose their speed given a specified cost function (the only restriction is that the cost function is a power function of speed) and the travel time costs are proportional to the wage. Furthermore, they show that the marginal effect of an exogenous environmental characteristic, such as weather, on the logarithm of speed can be interpreted as the marginal effect of this characteristic on the logarithm of the commuter’s total commuting costs (the sum of the travel time and other costs which vary with speed such as accidents cost and fuel costs). Given an estimate of average worker value of time, it is meaningful to estimate the effect on the welfare of commuters through a loss in travel time only. We will use a log specification in line with the theoretical considerations discussed in Van Ommeren and Dargay (2006). It takes the form:

$$\ln\left(S_{itd}\right) = \beta_0 + \beta_1 W_{itd} + \beta_2 \ln\left(D_{itd}\right) + \beta_3 \ln\left(y_i\right) + \beta_4 X_i + \beta_5 F_{td} + \xi_{itd} , \qquad (1)$$

where the β's are parameters to be estimated and subscripts *i* represent individuals, *t* represents hour of departure and *d* represents day of the year. *S* is speed, *W* is a vector of individual-specific time-varying variables (including weather variables), *D* denotes the distance travelled and *y* is the income of individuals, *X* is a vector of individual variables (including gender and age), *F* refers to time-specific characteristics such as urbanization, hour of travel, and seasonal variations, and ξ denotes an unobserved error term.

Using OLS for analysing the impact of weather on the speed of commuting trips is not ideal since it assumes that the residuals are uncorrelated. We face two shortcomings if we employ OLS estimation for equation (1). First, OLS does not control for differences in unobserved preferences of individuals and differences in other unobserved features (such as the exact location of the individual). We therefore exploit the panel structure inherent in the data to control for these issues. Specifically, we include individual fixed-effects in order to control for selection and unobserved heterogeneity.[6] Second, using OLS for analysing the impact of weather on the speed of commuting trips is not ideal since it assumes that the residuals are uncorrelated. This implies that if a person makes two trips on the same day the residuals from the model of both trips are assumed to be uncorrelated. This obviously does not hold in the current case.[7] As a result, OLS is inefficient (Wooldridge 2003). Therefore, a random effects panel data model that controls for the correlation between errors is employed.

Most of the variables included in model are self-explanatory. However, some other variables need additional explanation. We include personal characteristics, because they may effect the optimally chosen travelling speed to and/from access point. Furthermore, in this way we control for selection effects. The travel time of a trip may be different during peak and off-peak hours because of the difference in frequency of the service, difference in number of people using the public transport, etc. Therefore, a dummy variable is included for rush hours.[8] In order to control for congestion effects on roads for bus and tram trips we distinguish between trips on congested and non-congested roads. Specifically, we distinguish those trips that originate in non-congested areas during the morning peak hours and that are directed towards congested areas. Similarly, we distinguish those trips during evening peak hours that are directed from congested areas to non-congested areas (see Sabir *et al.* 2008). Ultimately, we include a congestion dummy variable that controls for these specific trips.

In order to analyse the effects of weather on travel time we use hourly measured wind strength, temperature, precipitation, snow and visibility. Dummy variables are used to measure the effects of most weather variables. Wind strength is measured by a dummy variable that represents wind strengths larger than 6 Beaufort.[9] We define three temperature categories, i.e., a dummy for temperatures less than 0 ^{o}C, a dummy for temperatures between 0 ^{o}C and 25 ^{o}C, and a dummy for temperatures higher than 25 ^{o}C. Precipitation effects are captured by using a dummy variable that is equal to one for the presence of precipitation during the hour in which the trip took place. The visibility variable measures the horizontal visible distance; a dummy is used to indicate a visibility distance less than 300 meters. We do not have exact measure of snow. However, we use interaction effects of temperature lower than or equal to 0 ^{o}C and presences of rain as a proxy for measuring snow. But, it may be noted that it is a crude measure of snow and this will only capture the effects of *falling* snow.

3. Results and discussion

3.1 Speed of bus, tram and metro trips

The estimation results are presented in Table 1. The results are robust and most of the variables have plausible signs. Observe that although temperature does not have a strong impact, snow, limited visibility and rain on congested routes all substantially reduce the speed of bus, tram and metro trips. Remember that trip speeds are computed on the basis of the sum of in-vehicle time and other time components, including access and egress times, waiting times and delays. Apparently, these three specific circumstances (snow, limited visibility and rain) cause an increase in travel time by affecting one or more of these components.

The fixed effects model shows that the speed of bus, tram and metro commuting trips is reduced by 12 percent in snow. A potential reason, at least for bus trips and maybe partly for tram trips, is that it is more risky to drive in snow and that the capacity of roads is reduced because of an increased distance between vehicles. Another reason may be that snow causes people to switch from biking and walking to public transport, thereby increasing the demand for public transport. This may cause that more and longer stopping and waiting times are required for passengers to enter and leave the vehicles. Although rain in general has no effect on trip speeds, it does have a substantial impact on trip speeds on already congested routes (making that the results are mainly driven by the effect of rain on the speed of bus trips). Specifically, rain reduces trip speed on congested routes by approximately 18 percent. This result is consistent with the result obtained in Sabir *et al.* (2008), who reported a 10-15 percent reduction in the speed of car commuting trips under the same circumstances. There also is a 6 percent reduction in trip speeds when visibility is under 300 meters (also this effect is likely driven by the effects of visibility on the speed of bus trips). This finding is plausible, as one would expect people and vehicle operators to change their behaviour under risky conditions such as limited visibility. The effects of other weather variables are small and, except for strong wind, statistically insignificant.

Table 1. Analysis of logarithm of speed of public transport commuting trips (individual specific effects) [a,b]

	Bus, Tram and Metro				Train			
	Fixed Effects		Random Effects		Fixed Effects		Random Effects	
	Coeff.	**S.E.**	**Coeff.**	**S.E.**	**Coeff.**	**S.E.**	**Coeff.**	**S.E.**
Strong Wind	**–.005**	.002	**–.004**	.001	.001	.001	.0003	.001
Temperature <= 0 °C	.02	.02	.01	.02	**.04**	.01	**.04**	.01
Temperature >25 °C	–.01	.02	–.01	.02	**–.04**	.01	**–.03**	.01
Rain	.01	.01	.01	.01	.003	.00	.005	.005
Snow	**–.12**	.04	**–.08**	.04	**–.06**	.02	**–.05**	.02
Limited visibility	**–.06**	.02	**–.06**	.02	.03	.02	.03	.02
Congestion x Rain	**–.18**	.05	**–.17**	.05	-	-	-	-
Congestion	*–.08*	.04	–.01	.01	-	-	-	-
Rush Hours	–.01	.01	*–.06*	.03	**.02**	.01	**.01**	.01
Distance	**.56**	.02	**.57**	.01	**.62**	.02	**.52**	.01
Gender (Males)	-	-	.01	.02	-	-	–.02	.01
Age less than 18 years	-	-	.04	.07	-	-	–.02	.09
Age between 30 and 40 years	-	-	.02	.03	-	-	**.05**	.02
Age between 40 and 65 years	-	-	–.01	.02	-	-	.02	.02
Age greater than 65 years	-	-	–.14	.12	-	-	*–.19*	.12
Weekdays	-	-	–.05	.04	-	-	–.01	.04
Very Urbanised	-	-	**–.11**	.04	-	-	**–.08**	.03
Urbanised	-	-	–.05	.04	-	-	–.04	.03
Moderately Urbanised	-	-	–.05	.04	-	-	.0004	.03
Little Urbanised	-	-	.02	.04	-	-	–.04	.04
Summer	-	-	.002	.02	-	-	.003	.01
Autumn	-	-	–.03	.02	-	-	.01	.01
Winter	-	-	**.05**	.02	-	-	–.01	.01
Constant	-	-	**1.66**	.06	-	-	**1.73**	.06
R^2	.95		-		.94			
Number of groups	1124		1124		1441		1441	
Variance of random error	-		.02		-		.01	
Variance of group specific error	-		.09		-		.06	
Correlation between error terms	-		.84		-		.83	

[a] Bold coefficients are statistically significant at 5%, italic coefficients are statistically significant at 10%.
[b] The reference categories for temperature, urbanisation, age, and seasonal variables, are temperature between 0 °C and 25 °C, rural, age between 18 and 30 years, and spring, respectively.

The effect of log distance on the speed of bus/tram/Metro trips is around 0.6, i.e. on average, trip speed increases by 0.6 per cent when distance increases by one percent. This makes sense because longer trips are likely to make more use of roads with higher speed limits than shorter trips. The congestion variable shows a reduction of 8 percent in trip speed, which is comparable to results by Sabir *et al.* (2008) who reported an 8 percent reduction in the speed of car commuting trips on congested routes. The effects of other characteristics on the speed of bus, tram and metro commuting trips are generally small and most are statistically insignificant. An exception is commuting trips made in highly urbanised areas, which are on average 11 percent slower compared to trips made in rural areas. This makes sense, since in these areas public transport is confronted with a larger number of crossings and traffic lights. Also the speed of the access mode (walking or cycling) to the public transport stop will be lower in highly urbanised areas.

Our analysis shows that snow, fog, wind and rain indeed have an impact on the speed of bus/tram/metro trips. Part of the explanation is that the speed of these vehicles themselves will be affected, implying increases in in-vehicle time. Another part of the explanation is that adverse weather leads to longer waiting times at platforms, in particular when people miss a connection, and leads to longer access and egress times. Note also that adverse weather has a doubly negative effect on integrated public transport: not only does it lead to longer and less reliable travel times, but also the comfort at transfer points will be worse. This provides a challenge to operators that aim at offering integrated transport services. Time tables should be made in such a way that they are reasonably robust under conditions of adverse weather, and also the comfort levels at transfer points should be adequate under various weather conditions.

3.2 Speed of train trips

The results of the fixed effects model on the speed of train commuting trips show that at temperatures below 0 ^oC train trips are 4 percent faster than train trips made at temperatures between 0 ^oC and 25 ^oC. Similarly, train commuting trips made during temperatures higher than 25 ^oC are 4 percent slower compared to normal temperatures. Remember that trip speeds are computed on the basis of the sum of in-vehicle time and other time components, including waiting times, delays, access and egress times to get to the station by foot, bicycle, bus, car, etc. A likely explanation is therefore that people may prefer to walk or bike rather than use public transport to go to or from a train station. Another reason may be that demand for train trips is lower in cold weather, which may result in a smaller number of people on access points, implying lower probabilities of delays. Similarly, if demand for train trips is higher in warm weather, we would observe an increased probability of delays. The results furthermore show that also train trips are slower during snow; the speed reduction is around 5 percent. Comparing the effects of snow on the speed of bus, tram and metro trips on the one hand and train trips on the other shows that train trips are less affected by snow. This is not surprising given the technology of the train compared to the bus. Both types of trips share the possible delay during the access and egress mode, but the bus (and up to some extent trams) travel on road networks with other vehicles, whereas the train has a separate network. Trains will therefore suffer less congestion and one may expect a smaller effect of snow on the speed of train trips compared to the effect for other modes.

Again the effects of other characteristics are small and generally insignificant for train commuters. However, the age variable shows some interesting results. The results suggest that trips made by people in the oldest age category are 19 percent slower compared to trips made by younger people. This likely reflects that older people take more time to reach access points and spend more time transferring between trains. It is also possible that older people have less access to cars, so they have to use public transport even when they live further away from an access point. Another interesting finding is the speed reduction in very urbanised areas compared to rural area. This probably reflects a difference in access modes: residents of highly urbanised areas typically will not use the car to get to the railway station and other access modes are typically slower than the car.

We find that, compared to bus/tram/metro trips, the impact of weather on rail trips is considerably smaller. The main effect we observe relates to snow, and this most probably is a consequence of the impact of snow on the access and egress modes used, not on the railway trip itself. This robustness makes rail an attractive transport mode compared to bus/tram/metro, and also compared to the car. This does not mean that reliability is not an issue in rail trips, because it certainly is. It does mean that that weather is not an important factor here and that the negative effects of certain weather conditions on rail trips is confined to the comfort level at railway stations. Thus, from the perspective of adverse weather, the main challenge to railway operators that aim at high quality public transport services is to build railway stations that are comfortable under various weather conditions.

3.3 Welfare effects through changes in travel time

An important purpose of the current study is to assess welfare effects of weather through changes in travel time of public transport.[10] For this we use information on the average value of travel time. There is a vast empirical literature on the value of travel time (see, e.g., Small and Verhoef 2007). Based on a meta-analysis of 56 value-of-time estimates from 14 different countries, Waters (1996) finds an average ratio of value of time equal to 48 per cent of gross wage rate and a median ratio of 42 per cent for commuting trips made by automobile. In another review, Wardman (1998) finds similar values. In this paper we follow the standard literature on values of time and use 50 percent of hourly gross wages as our measure. In the

Netherlands the average gross hourly wage rate is about 18 €, implying a value of time of 9 € per hour (Statistics Netherlands).[11] The welfare effects are based on the estimates from the fixed effects models, and are obtained by taking the product of the percentage effects, the average travel time and the value of time. The results are presented in Table 2.

The highest welfare loss due to adverse weather is observed for bus, tram and metro trips. The welfare loss for these trips due to snow is 0.76 € per commuting trip per person.[12] Similarly, bus, tram and metro commuting trips made in rainy conditions and on congested routes experience a welfare loss of 1.78 € per commuting trip per person. Furthermore, the welfare loss due to limited visibility is around 0.38 € per commuting trip per person. The highest welfare loss for train trips is that of snow, which leads to a loss of 0.50 € per commuting trip per person. Additionally, train trips made during high temperatures experience a loss of 0.40 € per commuting trip per person. However, there is a gain of 0.40 € per commuting trip per person when trips are made during temperatures below 0 ^{o}C. Note that these calculations only address the travel time element, and disregard the comfort element of adverse weather. No doubt, comfort levels of waiting at platforms and walking to access points will be lower under such circumstances. It is beyond the scope of the present study to provide estimates for this aspect.

Table 2. Welfare effects of weather through changes in travel time

	Welfare loss/gain (in €)	
Variables	**Bus, Tram and Metro**	**Train**
Wind strength	–0.03	0
Temperature <= 0 ^{o}C	0	0.40
Temperature > 25 ^{o}C	0	–0.40
Rain	0	0
Rain x Congestion	–1.78	-
Snow	–0.76	–0.50
Visibility	–0.38	0

4. Conclusion

In this study we analyse the effects of weather on the speed of commuting trips made by public transport in the Netherlands. We use micro data at the trip level obtained from a national transportation survey for the Netherlands. The data cover trips made by bus, metro, tram and train during 2004 and 2005. Hourly measured weather data for this period are obtained from Royal Netherlands Meteorological institute. The weather and transport data are matched in such a way that each trip was assigned the weather data for the hour in which that trip took place and from the weather station that was nearest to the place of departure.

We estimate panel data models with individual specific fixed and random effects in order to control for possible selection problems and unobserved heterogeneity. We use a large number of variables in our model to explain the speed of public transportation. Our main interest, however, is in the effect of weather variables on the speed of public transport and the associated welfare effects.

In general, the results are robust and most of the coefficients have plausible signs. The results show that wind strength has only a small negative effect on the speed of bus, tram and metro commuting trips. Snow has a substantial negative effect on the speed public transport. The associated welfare loss is 53 eurocent per commuting trip per person made by train and 76 eurocent per commuting trip per person made by bus, tram and metro. Rain strongly affects the speed of bus, tram and metro commuting trips on congested routes. The associated welfare loss is 1.15 € per commuting trip per person.

Effects of other characteristics are generally absent. However, one interesting finding is that train trips made by older people are 19 percent slower than those made by younger people. This may indicate that older people have fewer options to take the car on their way to the train station. They may also walk slower to their final destination on the egress part of their trips. It may of course be that they are just less in a hurry, but one should not forget that in our analysis we focus on commuting trips.

In terms of integrated transport we find that the effects of weather on trip speed are relatively strong in the case of bus/tram/metro trips. They may well lead to changes in in-vehicle time, but most probably also in waiting times at transfer points. This implies a challenge to public transport operators to develop time tables and operating routines that lead to reasonably robust outcomes for travellers. In the case of railway trips the impact of weather on speeds is clearly smaller. For both types of trips a general observation is that the comfort of trips under adverse weather likely depends substantially on the quality of the facilities at transfer points such as bus stops and railway stations. This is one of fields where efforts to improve the quality of integrated transport should focus.

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Appendix A

Table A1. Descriptive statistics of variables included in the empirical analyses

	Bus/Tram/Metro		Train	
	Mean	S.D	Mean	S.D
Speed (km/hr)	21.19	11.29	38.17	14.93
Travel Time (h)	0.71	0.34	1.11	0.48
Travel Time Congested Areas (h)	1.10	0.34	-	-
Distance (km)[13]	15.63	13.15	43.34	29.10
Strong Wind	0.02	0.16	0.02	0.16
Temperature <= 0° C	0.05	0.22	0.05	0.23
Temperature >0 to <=25	0.93	0.26	0.93	0.25
Temperature >25	0.02	0.15	0.02	0.12
Rain	0.19	0.40	0.19	0.39
Snow	0.01	0.10	0.01	0.09
Visibility	0.02	0.14	0.01	0.11
Morning Peak Hours	0.45	0.50	0.47	0.50
Evening Peak Hours	0.37	0.48	0.40	0.49
Non Peak Hours	0.18	0.39	0.13	0.34
Weekday dummy	0.94	0.24	0.98	0.16
Spring	0.25	0.43	0.22	0.41
Summer	0.21	0.41	0.23	0.42
Autumn	0.32	0.46	0.34	0.47
Winter	0.22	0.42	0.21	0.41
Very Urban	0.37	0.48	0.23	0.42
Urbanised	0.30	0.46	0.41	0.49
Moderately Urbanized	0.11	0.32	0.21	0.41
Little Urbanised	0.13	0.34	0.09	0.29
Rural	0.09	0.28	0.05	0.22
Age less than 18 years	0.02	0.15	0.00	0.07
Age between 18 to 30 years	0.31	0.46	0.25	0.43
Age between 30 and 40 years	0.19	0.39	0.27	0.44
Age between 40 and 65 years	0.47	0.50	0.47	0.50
Age greater than 65 years	0.01	0.07	0.00	0.05
Male	0.42	0.49	0.59	0.49
Congestion	0.05	0.21	-	-
Congestion x Rain	0.01	0.08	-	-
Number of Observations	5126		8492	

Endnotes

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1 The Randstad consists of a ring of the four largest cities of the Netherlands (Amsterdam, Utrecht, Rotterdam and the Hague) and their surrounding areas. The population of the Randstad is over seven million inhabitants which is almost 50 per cent of the total Dutch population. The Randstad is the main centre of employment and business activities, so in the morning congestion occurs on roads towards the Randstad while evening congestion occurs on roads from the Randstad.

2 We combine trips made by bus, tram and metro for two main reasons. First, average speed, distance and travel time of trips made by bus, tram and metro were similar. Second, bus, tram and metro are mostly use for medium distance trips, unlike the train which is mostly used for long distance trips.

3 The exact number of individuals in the sample is 130,534. These people have reported 453,885 trips out of which 13,618 were made by public transport .

4 We have estimated the average distance as follows: The total land area of the Netherlands is 33,889 km2. Given the assumption that stations are homogenously spread over the country and each weather station covers a circle, the maximum distance is 18.78 km. The average distance of a circle is 2/3 of the maximum distance, so the average distance to a station is 12.52 km. Although there may be differences in rain-no rain conditions within this range, especially during the summer, this is the smallest range available for hourly weather conditions in the Netherlands.

5 We improve on the statistical analyses of Fosgerau (2005) and Van Ommeren and Dargay (2006) by explicitly taking the time dimension of the moment of travel (in time of days, hours) into account as well as unobserved heterogeneity of commuters.

6 Note that some commuters have two different distances on the same day, which allows us to identify the effect of distance using individual fixed-effects.

7 The correlation between the two errors is higher than 0.80 for all public transport modes.

8 Morning peak hours are from 06:00 to 10:00, evening peak hours from 16:00 to 18:00, and all other hours are off-peak hours.

9 The Beaufort scale (BFT) measures wind strength on a scale of 1 to 12. On this scale, 6 BFT represents powerful winds with a speed between 39 and 49 kilometers per hours (or 10.8 to 13.8 meters per second) over a period of at least 10 minutes. Similarly, 12 BFT represents a hurricane with wind speeds larger than 117 kilometers per hour (or larger than 32.6 meters per second).

10 The calculation for welfare effects are computed on a per person basis, implying that total welfare loss for a trip by train or bus should be multiplied by the average load factors. This holds for all welfare calculations in this study.

11 Gross wage is 19 euro for (whole population). It may be noted that the gross wage can be lower for bus commuters and a higher for train commuters. Therefore, results will be slightly biased.

12 There is a 12 percent reduction in speed of bus/tram/metro when it snows. This implies an increase of 0.0852 hours in average travel time (0.12 x 0.71 = 0.0852). Given a value of time of 9 € per hour, the welfare loss due to snow is 0.0852 x 9 € = 0.76 €.

13 This is average distance of the entire trip. This implies that it includes not only in-vehicle distance but also distance travelled by access/aggress modes. The average in-vehicle distance for bus/tram/metro trips and train trips is 13.1 km and 36.7 km, respectively.