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## Employers Transport Plans: Do They Change The Commuting Behaviour Of Workers?

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EMPLOYER TRANSPORT PLANS:  
DO THEY CHANGE THE COMMUTING BEHAVIOUR OF  
EMPLOYEES?

Laurent VAN MALDEREN<sup>1</sup>, Bart JOURQUIN<sup>1</sup>, Isabelle THOMAS<sup>2</sup>

**Abstract**

The aim of this paper is to find out whether an employer transport plan adopted by a company can change the commuting behaviour of its employees, and in that case which mobility measures influence their choice best. To achieve this objective, data of large scale survey among Belgian large companies performed in 2 different periods of times are used and analysed by means of econometrics tools. The modal shares of the main modes of transport used for commuting are estimated by means of both single equation models and a seemingly unrelated regressions (SUR) model where the equations of the modal shares are related by the error terms. The results of these 2 approaches are then compared and discussed.

Results show that a SUR model provides better fits and delivers estimates which are different from those of the single equations. It also comes out that modal choices in favour of the bicycle or of the train are more influenced by both the environmental characteristics of the workplace and its employer transport plan than modal choices in favour of the car or of carpooling. The financial incentives to the use of both the bicycle and the train increase their modal shares as well as strategies favouring their trials. The availability of some cycling facilities and the organization of carpooling by the company increase the modal shares of the bicycle and carpooling respectively. All these measures play an important role in the mobility management programs of companies.

*Keywords: commuting, employer transport plan, sustainable commuting, Belgium*

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## 1. Introduction

In recent years, the interest of companies for the home-to-work travels of their employees has steadily increased through both public policies aiming at the involvement of the companies in the mobility debate and business objectives mobility can achieve. In fact, governments have developed initiatives which made compulsory (e.g. the *'travel plans ruling'* of the Brussels-Capital Region in Belgium) or encourage (e.g. the *'Transport White Paper'* in the United Kingdom; DETR, 1998) the implementation of Employer Transport Plan (ETP) within the companies. In addition to address the growing environmental issue, ETPs can also be used as a tool to improve the corporate social responsibility of their company or to aim at operational benefits (e.g. reducing parking costs or attracting staff; Roby, 2010; Winters and Hendricks, 2003). As a result, a growing number of companies have implemented an ETP.

The increase in the number of companies with an ETP is accompanied by a growth in the attention paid by the literature to their impact on the commuting behaviour of their employees. Numerous researches have tackled the issue by specifically analysing ETPs (e.g. Nozick *et al.*, 1998; Cairns *et al.*, 2010; Van Malderen *et al.*, 2012) or in the framework of other analysis (e.g. De Witte *et al.*, 2008; Van Exel and Rietveld, 2009; Vanoutrive *et al.*, 2012a). However, the literature often focuses on the analysis of either a specific mode of transport (e.g. Dickinson *et al.*, 2003; Vanoutrive *et al.*, 2012b) or a specific type of mobility measures (e.g. Rye and Ison, 2005; Marsden, 2006; Buliung *et al.*, 2011). Hence, the aim of this paper is to find out which mobility measures change commuting behaviour by jointly analysing the modal shares of the main modes of transport used for commuting. To achieve this objective, data of the Belgian *'Home-To-Work Travels'* (HTWT) diagnosis are analysed.

The structure of the paper is the following. First, the methodology is described (Section 2). Section 3 then presents the data and Section 4 the results. Section 5

discusses the results and finally Section 6 concludes the paper in the form of policy recommendations.

## 2. Methodology

Two successive models are estimated. First, the modal shares are explained with Single Equation (SE) models. Then, a Seemingly Unrelated Regressions (SUR) model is used in order to estimate the modal shares jointly. Finally, the results of these 2 models are compared.

### 3.1. Single equation model

Let  $y_{it,m}$  be the modal share of the mode of transport  $m$  in workplace  $i$  at time  $t$ . One can assume that this modal share is depending on characteristics of both the workplace (e.g. on-site car park scarcity or mobility measures making up the ETP implemented) and its environment (e.g. accessibility to railway-stations). If  $x_{it,k}$  is the observed characteristic  $k$  related to the workplace  $i$  at time  $t$ , the SE model can be written:

$$y_{it,m} = \alpha + \sum_k \beta_k x_{it,k} + \delta_t + \varepsilon \quad (1)$$

where  $\varepsilon$  is a random error term assumed to be identically-distributed, and  $\delta_t$  is a time-period dummy. In fact, 2 periods of time are available in our data and therefore the choice has been made to conduct a pooled analysis. Equation (1) can be estimated by Ordinary Least Square (OLS; Wooldridge, 2002). However, all the environmental characteristics influencing the modal choices of the employees are not observed. As the workplaces which are neighbours share the same environmental characteristics, this will result in correlated effects among observations spatially close (Manski, 1993). In addition, one can also expect that the employees of the companies which are neighbours adopt similar commuting behaviours. Consequently data are highly suspected to be spatially autocorrelated.

This phenomenon violates the assumptions of the OLS model and requires the use of spatial econometrics tools.

Generally, there are 3 ways for taking into account spatial autocorrelation: introducing spatially lagged exogenous variables, introducing a spatial lag of the endogenous variable (the so called spatial lag model), or introducing a spatially autocorrelated error term (the so called spatial error model; Le Gallo, 2002). The most commonly used specifications are the spatial lag and the spatial error models though the spatial variables can be combined (e.g. Zhou and Kockelman, 2009; Adjemian *et al.*, 2010). However, the introduction in the same model of the 3 types of spatial variables is not possible because parameters are then unidentified (Manski, 1993). Therefore, if the true data-generation process combines these 3 spatial variables (i.e. the so called Manski model), Lesage and Pace (2009) advice to exclude the spatially autocorrelated error term because it will only cause a loss of efficiency. Moreover, ignoring explanatory variables will produce biased and inconsistent estimators (Greene, 2005; Elhorst, 2010). This leads to the Spatial Durbin model which incorporates the spatial lag of the exogenous variable and of the endogenous variables. The spatial Durbin model of a pooled model can be written as follow:

$$y_{it,m} = \alpha + \rho W y_{it,m} + \sum_k \beta_k x_{it,k} + \sum_k \gamma_k W x_{it,k} + \delta_t + \varepsilon \quad (2)$$

where  $\varepsilon$  is a random error term assumed to be identically-distributed, and  $W$  is a spatial weight matrix which describes the spatial arrangements of the observations of the sample (Elhorst and Fréret, 2009). As we work at the workplace level and hence data points, a distance threshold based weight matrix is used. The neighbours of a workplace are all workplaces which are located within a certain threshold distance. This threshold distance is defined empirically: weight matrices with different distances are first tested and then the weight matrix which minimises the information criteria is selected because it has the highest probability to identify the true specification of the weight matrix (Stakhovych and

Bijmolt, 2009). The Akaike Information Criterion (AIC) and the Schwarz Information Criterion (SIC) are used here for this purpose. Note that this weight matrix  $W$  is row-standardised so that  $\sum w_{ij}y_{jt,m}$  represents for each workplace  $I$  the average modal shares of the mode of transport  $m$  of the workplaces located within the threshold distance. In the same way,  $\sum w_{ij}x_{jt,k}$  represents for each workplace the mean of the exploratory variable  $k$  of the workplaces located within the threshold distance.

Two factors speak in favour of the spatial Durbin model. First, it produces unbiased coefficient estimators also if the true data-generation process is any other spatial specification, with the exception of the Manski one (Elhorst, 2010). Secondly, this model is a special case of both the model with the spatial lag of the endogenous variable only (i.e. the spatial lag model) and the model with an autocorrelated error term only (i.e. the spatial error model)<sup>3</sup>. Consequently, the spatial Durbin model can be used in order to perform specification tests and to find out the true spatial process of the data as advised by Elhorst (2010). The spatial Durbin model is estimated by Maximum Likelihood (ML) here.

### 3.2. Seemingly Unrelated Regressions

A SE model is estimated for each mode of transport used for commuting. However, these models analyse each mode of transport individually. In order to analyse them jointly, a Seemingly Unrelated Regressions (SUR) model is used. A SUR model relates each equation by their error terms. In fact, the errors terms in the different equations are correlated in a SUR model. There are 3 main advantages to use such a specification compared to a SE models. First, the correlation of the errors among the equations is an assumption which seems to be more reasonable than the assumption of independency of the errors of the SE models. In fact, the modes of transport are competing with each other and are thus

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<sup>3</sup> In fact, the spatial Durbin model is reduced into the spatial lag model when  $\gamma_k=0$  and into the spatial error model when  $\gamma_k=\rho\beta_k$  (Adjemian *et al.*, 2010).

related. Secondly, a SUR model can reflect some immeasurable or omitted factors common to the equations (Greene, 2005; Allers and Elhorst, 2010). This is the case here as the modal shares are analysed at the workplace level. Consequently, potential unobserved or omitted variables will have explanatory power for each mode of transport analysed as they are competitors. Thirdly, it allows efficiency in the estimation to be gained (Binkley and Nelson, 1988). The SUR specification of Equation (2) can be written as follow:

$$\begin{aligned}
 \mathbf{Y}_m &= \alpha_m + \rho_m \mathbf{W} \mathbf{Y}_m + \beta_m \mathbf{X}_m + \gamma_m \mathbf{W} \mathbf{X}_m + \delta_m + \varepsilon_m \\
 E[\varepsilon_m' \varepsilon_m / \mathbf{X}_1, \mathbf{X}_2, \dots, \mathbf{X}_m] &= \mathbf{\Omega}
 \end{aligned}
 \tag{3}$$

where  $m$  is the equation index,  $\mathbf{Y}_m$  is the vector of response variables for equation  $m$ , and  $\mathbf{X}_m$  is a  $n$  by  $k$  matrix of explanatory variables for equation  $m$ . Note that the number of variables  $k$  do not have to be the same across the equation (Zhou and Kockelman, 2009) and that the weight matrix,  $\mathbf{W}$ , may also vary among the equations (Mur *et al.*, 2010). In the same way, the spatial specification of each equation may differ as the spatial Durbin model is a special case of both the spatial lag and the spatial error models. In that last case, constraints on the coefficients of the equation has to be set. The SUR model is estimated by ML.

### 3. Data set

The HTWT diagnosis is a large scale survey performed in Belgium by the federal public service '*Mobility and Transport*'. Every 3 years, each company located in Belgium that employs at least 100 employees has to fill in a mobility questionnaire for every of its workplaces of more than 30 employees. The mobility questionnaire consists of questions about the modal choice of employees, the ETP implemented within the company, the mobility problems faced by the employees and the workplace and its characteristics. Two diagnoses are available to date: the first which took place in 2005 and the last which was performed in 2008. In total, these 2 diagnoses contain data about respectively 7,460 and 9,455

workplaces. However, only 4,559 workplaces are common in both diagnoses. Data on those workplaces are used in this paper. Thus, the total number of observations is 9,118. The database is further enriched with data on:

- the functional urban regions (namely city centre, built-up area, suburb, industrial area and other defined by Luyten and Van Hecke, 2007) in which the workplace is located,
- the average slope computed on the roads within each municipality where the workplace is located (Vandenbulcke *et al.*, 2011);
- the average potential population that can reach by car within a certain time threshold the centre of the municipality where the workplace is located (Vandenbulcke *et al.*, 2007);
- the households' satisfaction with cycling facilities of the municipality where the workplace is located. This satisfaction with cycling facilities was evaluated during the 2001 Belgian census (Statbel);
- the accessibility by rail of each workplace. It consists of the sum of the average walking time from the workplace to the 5 nearest railway stations and of the average waiting time at these stations (Vanoutrive *et al.*, 2012a).

Appendix 1 provides some descriptive statistics about the modal splits and the characteristics of the workplaces surveyed in both the 2005 and 2008 HTWT diagnoses. Note that the on-site car parking scarcity and the on-site bicycle parking scarcity is defined here as the probability an employee has to find a free park. Thus, these variables are calculated by dividing the number of on-site car (or bicycle) parks by the number of employees and if the result is larger than 1, a value of 1 is assigned in order to reflect a probability. Appendix 1 also shows that between 2005 and 2008 the average modal shares of the car and the one of carpooling have slightly decreased, while those of the train, the public transport and the bicycle have slightly increased. The standard deviations, the minimum and maximum values of the variables also show that a lot variance exists within the workplaces surveyed in the HTWT diagnoses and in the commuting behaviour



of their employees. As regards with the ETP and the mobility problems faced by the workplaces, descriptive statistics on the variables available in the HTWT database are not reported here for reason of space. They are all binary variables which reflect if the workplace has implemented the mobility measure or not, and if the workplace faces the mobility problem or not. Note however that the diagnosis takes into consideration 15 types of measures favouring the use of cycling, 6 favouring carpooling, 6 favouring public transport and 11 miscellaneous mobility measures (for more information about the mobility measures as well as about the mobility problems faced by the workplaces see Van Malderen *et al.*, 2012). The most popular measures are the additional payment for cycling commuting, the provision of covered bicycle storages, the provision of secured bicycle storages, the provision of showers, the provision of bicycle repair facilities, and the additional payment for using public transport. Finally, note that the companies of the sample have in average increased their interest in mobility during the studied period. In fact, the average number of mobility measures implemented per workplace was 3.03 in 2005 and 3.82 in 2008. In addition, the number of workplaces without any measures has decreased from 19.78 percent of the sample in 2005 to 14.67 percent in 2008.

#### **4. Results**

First, 4 SE models are estimated by OLS. The variables to explain are the modal shares of the car, the train, the bicycle and the carpool respectively. The other modes of transport are not analysed here because we are lacking data about their explanatory variables (e.g. bus accessibility) and/or because they are not promoted by the workplaces (e.g. motorbike). The modal share of walking is also not explained because walking implies very small distances which do not match our variables. The explanatory variables are the characteristics of the workplaces (see table 1), the characteristics of their environment related to the mode of transport analysed (see table 1), mobility problems faced by the employees of the workplaces, and finally mobility measures promoting the mode of transport of the equation. Note that in the “*car model*”, the mobility measures included in the

equation are all the mobility measures of the other equations as they are supposed to reduce the modal share of the car.

Secondly, the Lagrange Multiplier (LM) tests and their robust counterparts are performed on the residuals of the OLS. As advised by Elhorst (2010), the spatial Durbin model is estimated if the tests reject the OLS model in favour of the spatial lag, the spatial error model or in favour of both models.

Thirdly, Likelihood Ratio (LR) tests are used in order to discriminate among the 3 spatial specifications. Note that, for each SE, the weight matrix that minimises the information criteria is selected. These 3 steps allow the specification of each equation to be found out. Finally, a SUR model is estimated where each equation follows the specification of the SE analysis.

Table 2 and 3 present the regression diagnostics of the estimations. The regressions diagnostics of the SE estimations (table 2) show that for each mode of transport the specification tests point out the spatial Durbin model as the specification to favour. In fact, this model outperforms the OLS one (equation (1)), but also spatial lag and spatial error specifications. The weight matrices which are used are those which minimise the information criteria. A different weight matrix has to be used for each mode of transport. Consequently, the estimated SUR model (table 3) includes 4 spatial Durbin equations with a different weight matrix for each equation. Note however that the spatial Durbin models estimated here only consider the spatial lag of the continuous variables. In fact, the spatial lags of the binary variables are not included because they make singular the matrix of explanatory variables,  $\mathbf{X}_m$ . As regards with the quality adjustment of the estimations, the results show that a joint estimation of the 4 modal shares improves the likelihood of the estimators. In fact, the log likelihood value of the SUR estimation (-40219) is higher than the sum of the log likelihood values of the spatial SE estimations (-42891). In addition, the squared correlations between the observed and the fitted values (corr) are higher for the separate

equations of the SUR than for the SE. On the contrary, the  $R^2$  of the spatial SE and of the separate equations of the SUR are similar. However, the  $R^2$  have to be interpreted with caution as their interpretation may be misleading in the presence of spatial effects and when the model is estimated by ML (Anselin, 1988). Note that the  $R^2$  as well as the squared correlations between the observed and the fitted values show that our data explains the modal shares of the bicycle and of the train best.

Table 2 – Regression diagnostics for the SE estimations

	OLS				Spatial Durbin			
	Car	Bicycle	Train	Carpool	Car	Bicycle	Train	Carpool
Log likelihood	-7094	-11100	-12629	-12068	-6807	-10356	-11665	-11997
AIC	14295	22280	25316	24194	13745	20812	23406	24070
SIC	14673	22564	25522	24400	14208	21167	23676	24340
$R^2$	0.22	0.54	0.41	0.18	0.27	0.61	0.55	0.19
Corr	0.22	0.54	0.41	0.18	0.24	0.59	0.47	0.19
LM test (error)	471.70***	3647.62***	1380.95***	53.75***	-	-	-	-
LM test (lag)	114.45***	3159.13***	2109.45***	55.81***	-	-	-	-
Robust LM test (error)	372.97***	1101.26***	19.16***	0.08	-	-	-	-
Robust LM test (lag)	15.72***	612.77***	747.67***	2.14	-	-	-	-
LR test (error)	-	-	-	-	454*	108*	154*	88*
LR test (lag)	-	-	-	-	189*	230*	608*	84*
Distance threshold of the weight matrix (in meter)	-	-	-	-	3000	10000	1000	1500

Note: i) Significant at \*0.10 \*\*0.05 \*\*\*0.01

Table 3 – Regression diagnostics for the SUR estimation

	System		Mode of transport			
	MacElroy's $R^2$	Dhrymes' $R^2$	Car	Bicycle	Train	Carpool
$R^2$	0.44	0.46	0.27	0.61	0.54	0.19
Corr	-	-	0.27	0.61	0.54	0.19
Log likelihood value	-40,219					

Table 4 and 5 compare the coefficient estimates and the standard deviation estimates of the SUR model and of the spatial Durbin SE models. The comparison is based on the ratio between the SUR and the SE estimates. This ratio has to be interpreted as follows. A value of 1 indicates that both SUR and SE models give

exactly the same result; a value smaller than 1 indicates that the SUR estimates is lower than its SE counterpart, and a value larger than 1 indicates that the SUR estimate is higher than the SE one. Finally, the absolute difference of the ratio and 1 gives the relative difference (in %) between the SUR and the SE estimates. We observe that the coefficient estimates are rather similar for the ETP variables, with the exception of those of the car equation. In fact, the mean and the median of the ratios between the SUR and SE coefficient estimates of the ETP variables are close to 1 and the standard deviation of these ratios is close to 0 for the bicycle, the train and the carpool equation (table 4). On the contrary, the dissimilarity is more important for the coefficients of the variables related to the mobility problems, the company and its environment and the other type of variables. The largest differences in the coefficients estimates are observed for the time-period dummies and the intercepts. This is probably explained by the immeasurable or omitted factors common to all equations the SUR model takes into account.

Table 4 – Comparison between the SUR and SE coefficient estimates

Mode of transport	Type of variable	Ratio between SUR and SE coefficient estimates				
		Minimum value	Maximum value	Mean	Median	Std. Dev.
Car	Spatial lag <sup>a</sup>	0.97	0.97	0.97	0.97	-
	ETP	0.25	2.07	1.08	1.05	0.45
	Mobility problems	0.88	1.63	1.06	1.03	0.21
	Company and its environment	0.73	2.30	1.12	0.96	0.46
	Other	0.51	5.86	1.22	0.99	1.22
	<i>Total</i>	<i>0.25</i>	<i>5.86</i>	<i>1.12</i>	<i>0.99</i>	<i>0.71</i>
Bicycle	Spatial lag <sup>a</sup>	1.02	1.02	1.02	1.02	-
	ETP	0.95	1.02	0.99	0.99	0.02
	Mobility problems	0.98	1.11	1.01	1.00	0.04
	Company and its environment	0.95	1.18	1.04	1.01	0.07
	Other	-21.77 <sup>b</sup>	1.89	-0.49	0.99	5.89
	<i>Total</i>	<i>-21.77<sup>b</sup></i>	<i>1.89</i>	<i>0.62</i>	<i>0.99</i>	<i>3.02</i>
Train	Spatial lag <sup>a</sup>	0.91	0.91	0.91	0.91	-
	ETP	0.97	1.06	1.02	1.02	0.03
	Mobility problems	0.92	1.94	1.17	1.04	0.31
	Company and its	0.99	1.12	1.07	1.10	0.05

	environment					
	Other	0.92	1.07	1.00	1.02	0.04
	<i>Total</i>	<i>0.92</i>	<i>1.94</i>	<i>1.06</i>	<i>1.03</i>	<i>0.17</i>
Carpool	Spatial lag <sup>a</sup>	0.99	0.99	0.99	0.99	-
	ETP	0.97	1.02	0.99	0.99	0.02
	Mobility problems	0.59	1.00	0.95	0.99	0.13
	Company and its environment	0.90	1.35	1.06	1.00	0.16
	Other	0.33	2.52	1.17	0.99	0.58
	<i>Total</i>	<i>0.33</i>	<i>2.52</i>	<i>1.06</i>	<i>0.99</i>	<i>0.33</i>
All	Spatial lag <sup>a</sup>	0.91	0.91	0.97	0.98	0.05
	ETP	0.25	2.07	1.04	0.99	0.31
	Mobility problems	0.59	1.94	1.05	1.00	0.21
	Company and its environment	0.73	2.30	1.08	1.00	0.26
	Other	-21.77 <sup>b</sup>	5.86	0.73	1.00	3.04
	<i>Total</i>	<i>-21.77<sup>b</sup></i>	<i>5.86</i>	<i>0.95</i>	<i>1.00</i>	<i>1.68</i>

<sup>a</sup> Spatial lag of the endogenous variable

<sup>b</sup> This minimum value is the ratio between the intercept estimated in the SUR model and the one estimated in the bicycle SE. It is the only variable whose estimate sign changes between the 2 models.

As regards the standard deviations estimates, table 5 shows that globally the SUR model does not deliver more precise estimators. In fact, the ratio between the standard deviation estimates of the SUR model and those of the SE ones are on average identical while the coefficient estimates are lower (see above). This observation is particularly true for the estimates of the spatial lags of the endogenous variables: their coefficients are lower in the SUR model and their standards deviations are higher. The ETP variables are not affected by this relative loss in efficiency: the results of both models are nearly identical. Table 5 also shows that with the exception of the car equation the statistical inferences performed on the basis of the estimates are similar between the SUR and the SE models. The inference performed for the ETP variables are also similar in the SUR and in the SE models: the same ETP variables are significant in the bicycle, train and carpool equations.

Table 5 – Comparison between the SUR and SE standard-deviation estimates

Mode of transport	Type of variable	Percentage of unchanged Inference <sup>b</sup>	Ratio between SUR and SE coefficient estimates				
			Minimum value	Maximum value	Mean	Median	Std. Dev.
Car	Spatial lag <sup>a</sup>	100	1.28	1.28	1.28	1.28	-
	ETP	77.78	0.94	0.99	0.95	0.94	0.01
	Mobility problems	100	1	1	1	1	0
	Company and its environment	90.90	0.94	1.01	0.98	0.99	0.03
	Other	87.5	0.86	1.16	1	1	0.07
	<i>Total</i>	<i>86.1005</i>	<i>0.86</i>	<i>1.28</i>	<i>0.98</i>	<i>0.97</i>	<i>0.06</i>
Bicycle	Spatial lag <sup>a</sup>	100	1.37	1.37	1.37	1.37	-
	ETP	100	1	1	1	1	0
	Mobility problems	100	1	1	1	1	0
	Company and its environment	100	0.99	1.01	1	1	0
	Other	93.33	0.97	1.15	1.01	1	0.04
	<i>Total</i>	<i>96.50</i>	<i>0.97</i>	<i>1.37</i>	<i>1</i>	<i>0.99</i>	<i>0.06</i>
Train	Spatial lag <sup>a</sup>	100	1.37	1.37	1.37	1.37	-
	ETP	100	1	1.01	1.01	1.01	0
	Mobility problems	100	1	1.01	1.01	1.01	0
	Company and its environment	100	0.98	1.01	1	1	0.01
	Other	92.86	0.98	1.05	1	1	0.02
	<i>Total</i>	<i>97.43</i>	<i>0.98</i>	<i>1.37</i>	<i>1.01</i>	<i>1.01</i>	<i>0.06</i>
Carpool	Spatial lag <sup>a</sup>	100	3.40	3.40	3.40	3.40	-
	ETP	100	1	1	1	1	0
	Mobility problems	100	1	1	1	1	0
	Company and its environment	100	0.99	1	1	1	0
	Other	100	0.99	1.03	1	1	0.01
	<i>Total</i>	<i>100</i>	<i>0.99</i>	<i>3.40</i>	<i>1.06</i>	<i>1</i>	<i>0.35</i>
All	Spatial lag <sup>a</sup>	100	1.27	3.40	1.85	1.37	1.03
	ETP	89.28	0.94	1.01	0.98	1	0.02
	Mobility problems	100	1	1.01	1	1	0
	Company and its environment	97.22	0.94	1.01	0.99	1	0.02
	Other	93.22	0.86	1.16	1	1	0.04
	<i>Total</i>	<i>94.39</i>	<i>0.86</i>	<i>3.40</i>	<i>1.01</i>	<i>1</i>	<i>0.18</i>

<sup>a</sup> Spatial lag of the endogenous variable

<sup>b</sup> The percentage of unchanged inference is the percentage of variables whose significance (or non-significance) does not change between the SUR and the SE model. The significance is evaluated at the 0.05 level.

All estimated coefficients and their  $t$ -values are not reported here<sup>4</sup>. Table 6 reports the results of the SUR model for the variables related to the ETP of the workplaces. They show that the measures that increase the use of cycling to work are the additional payment for cycle commuting, the additional payment for work trips, the availability of bicycles for commuting and for work trips, the provision of rain clothes, the availability of covered bicycle storages and the availability of bicycle repairs facilities. On the contrary, the results show that the availability of secure bicycle storages and the availability of bicycles at the railway stations decrease the modal shares of the bicycle. The former measures are perhaps taken at inappropriate workplaces (e.g. with poor cycling infrastructure). The negative effect of the latter, namely the availability of bicycles at the railway station, can have 2 explanations. First, in the HTWT diagnosis, only the main mode of transport for commuting is asked for. Thus, one can assume that for instance in the case where a commuter uses a bicycle made available at a railway station, she/he is counted as a train user. Secondly, this can also show that the multimodality train and bicycle is actually not an option in Belgium. The measures which favour the use of public transport are the additional payment for using public transport, the diffusion of information about public transport and the encouragement to use public transport for work trips. Finally, the organisation of carpooling by the company increases the number of carpoolers.

Table 6 – Results of the SUR estimation for the ETP variables

Equation	Variable	Parameter	Standard Deviation	T-stat
Bicycle	Additional payment for cycling commuting***	0.18	0.02	10.83
	Secure bicycle storage**	-0.04	0.02	-2.32
	Additional payment for work trips by bicycle**	0.07	0.03	2.28
	Making bicycles available for commuting***	0.24	0.07	3.68
	Making bicycles available at the railway station***	-0.29	0.09	-3.35
	Making bicycles available for work trips***	0.28	0.03	9.70

<sup>4</sup> They are available upon request to the first author of this article.

	Provision of rain clothes***	0.24	0.06	3.76
	Improvement of the infrastructure	0.04	0.05	0.83
	Covered bicycle storage***	0.10	0.02	5.10
	Provision of a changing room	-0.04	0.03	-1.41
	Showers	-0.01	0.03	-0.32
	Bicycles repair facilities*	0.07	0.04	1.68
	Bicycles maintenance facilities	0.12	0.07	1.65
	Diffusion of information about cycling routes	-0.05	0.05	-1.09
	Other cycling measures	-0.01	0.03	-0.46
Train	Additional payment for using public transport***	0.08	0.02	3.54
	Coordination with public authorities	0.05	0.04	1.28
	Diffusion of information about public transport**	0.09	0.03	2.89
	Encouragement to use public transport for work trips***	0.29	0.04	8.16
	Public transport measures: other***	0.09	0.03	2.92
Carpooling	Organisation of carpooling***	0.29	0.04	7.03
	Carpooling database*	-0.08	0.04	-1.69
	Reserved car parks for carpoolers	0.09	0.06	1.45
	Guarantee for the return journey	0.03	0.07	0.46
	Diffusion of information about carpooling	-0.03	0.05	-0.59
	Carpooling measure: other***	0.15	0.04	3.00

Note: i) Significant at \*0.10 \*\*0.05 \*\*\*0.01

## 5. Discussion

The comparison between the SE and SUR models shows that the modal shares are best statistically explained when they are estimated jointly. A joint estimation of the modal shares also leads to different estimates than those obtained with SE estimations. Therefore, the statistical inferences performed in order to find out the significant explanatory variables also leads to different results and operational conclusions. This implies that, in our case, the modal share of one mode of transport cannot be analysed aside from the others: they are competitors and hence tightly related. The econometrics specification used to explain the modal shares have thus to take this relationship into account. SUR models can achieve this objective by relating each equation by their error terms. However, one can go further and relate each equation by cross-equation restrictions. In fact, the model



estimated in this paper does not ensure that the sum of the modal shares equals one. In the same way, it does not ensure that the coefficient estimates are symmetric across the equations. In fact, a variable increasing the use of one mode of transport has to decrease the use of the other modes of transport by the same number of commuters. Thus, estimating a model with an adding-up constraint and/or with a symmetry one as in Elhorst and Oosterhaven (2006) could be interesting in the future.

Interestingly, the modal shares which are the best explained are those of bicycle and train. This result puts into perspective those of Meurs and Haijjer (2001) who stated that the modal choices are mainly explained by the personal characteristics of the commuters (e.g. their age or income). In fact, this seems to be less the case for modal choices in favour of bicycle or train than for those in favour of the car and carpooling: the former are more influenced by the environmental characteristics of the workplaces and by their ETP than the latter. This confirms Van Malderen *et al.* (2012): the promotion of bicycle and train would be more likely to be successful than the promotion of carpooling.

As regards with ETP, results show that some mobility measures can change the commuting behaviour of employees. In conformity with the literature on both ETP and commuting (Kingham *et al.*, 2001; Dickinson *et al.*, 2003; De Witte *et al.*, 2008; Cairns *et al.*, 2010), the financial incentives to the use of alternative modes of transport to the car and the availability of some cycling facilities increase the number of cyclists and of train users. As find by Van Malderen *et al.* (2012), the strategies favouring trials of these modes also increase their modal share. Unlike Buliung *et al.* (2011), we do not find a positive effect on carpooling of the availability of an emergency ride home service or of carpool parking spaces. The creation of a carpool database within the company or the subscription to a carpool database does not increase its use. On the contrary, companies that organize carpooling for their employees have more carpoolers. This result may be explained by a form of inertia among employees. In fact, carpooling depends on

being able to find a partner to travel with (Van Malderen *et al.*, 2012) and employees are probably not enough proactive in that process. Thus, carpooling meets more success when a part of the process is performed by the company itself.

## **6. Conclusion**

This paper aims at finding which mobility measures taken by the employers are susceptible to change the commuting behaviour of employees. To achieve this, data of a Belgian large scale survey performed at 2 periods of time are used and the modal shares of 4 modes of transport (i.e. car, bicycle, train and carpooling) are analysed by means of econometrics tools. We find that companies can really have an impact on the commuting behaviour of their employees. It also comes out that the financial incentives to the use of both the bicycle and the train, the availability of some cycling facilities at the workplace and the organization of carpooling by the company have the potential to convince the employees to give up the car. Consequently, a special attention should be paid to include these aspects in the mobility management programs of companies.

The results also show that the econometrics models used to estimate the modal shares should take their relationship into account. Indeed, the modes of transport are mostly competitors and their modal share should not be analysed aside from the others. In this respect, seemingly unrelated regressions seem to be a promising tool to achieve this objective.

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Appendix 1 – Statistics about the workplaces of the HTWT diagnoses

Variables	Diagnosis							
	2005				2008			
	Mean	Std. Dev.	Min	Max	Mean	Std. Dev.	Min	Max
Modal shares								
Car	69.08	22.64	0	100	67.9	23.48	0	100
Carpooling	3.46	8.13	0	100	2.84	6.52	0	92.80
Train	6.53	13.43	0	98.90	7.04	14.05	0	92.20
Public transport	5.54	9.66	0	72.50	6.11	10.36	0	78.70
Bicycle	8.25	10.26	0	83.80	8.99	10.83	0	81.40
Other <sup>a</sup>	7.14	10.65	0	100	7.12	11.57	0	100
Number of employees	204.19	374.43	30.00	6552.00	209.52	363.58	30.00	6842.00
Working schedule <sup>b</sup>								
Fixed	33.86	37.59	0	100	32.16	37.42	0	100
Shift	13.33	25.03	0	100	12.03	23.94	0	100
Irregular	20.15	36.24	0	100	19.63	35.78	0	100
Chosen by the employee	25.26	37.80	0	100	26.78	38.75	0	100
Other	7.34	23.36	0	100	9.40	20.72	0	100
Average slope <sup>c</sup>	2.19	1.27	0.68	10.29	2.19	1.27	0.68	10.29
Population potential <sup>c</sup>	1.17	0.24	0.39	1.66	1.17	0.24	0.39	1.66
Type of urban area <sup>d</sup>								
City centre	0.37	0.48	0	1	0.37	0.48	0	1
Agglomeration	0.20	0.41	0	1	0.20	0.41	0	1
Suburbs	0.09	0.29	0	1	0.09	0.29	0	1
Industrial zone	0.13	0.34	0	1	0.13	0.34	0	1
Other	0.20	0.40	0	1	0.20	0.40	0	1
Households' satisfaction with cycling facilities <sup>c</sup>	50.89	20.76	5.09	104.40	50.89	20.76	5.09	104.40
Rail accessibility <sup>e</sup>	-0.03	1.02	-7.48	1.12	-0.03	1.02	-7.48	1.12
Car park scarcity	0.52	0.35	0	1	0.53	0.35	0	1
Bicycle park scarcity	0.15	0.20	0	1	0.16	0.21	0	1

<sup>a</sup> The other modes of transport are: walking, motorbike, and transport organised by the employer.

<sup>b</sup> The working schedule variables consist of the percentage workforce which works a specific schedule arrangement.

<sup>c</sup> Variables calculated at the municipality level.

<sup>d</sup> Binary variables.

<sup>e</sup> Standardised variable.