Spatial modelling of origin-destination commuting flows in Switzerland

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1. Objective and methodology

This paper presents a direct modelling approach for origin-destination (OD) public transportation commuting flows for the case of Switzerland. Its purpose is to improve the gravity modelling approach for OD flows by applying a spatial autoregressive regression model, testing different spatial weighting schemes and accounting for endogeneity aspects. To the best of our knowledge, there has been no prior application of such advanced models in the context of transport demand modelling for public transport. Methodologically, in the first step a gravity model is developed and tested for the presence of spatial autocorrelation in its residuals. Subsequently, variants of a spatial lag model with different spatial weighting schemes are developed. Furthermore, we test the inclusion of an endogenous variable defined as the mean income differences between the interacting regions on its ability to describe interregional demand patterns. In addition, we treat for the endogenous nature of the newly constructed variable. Last, we are also testing its ability to serve as the basis for the construction of the spatial weight matrix, thus replacing the commonly used travel time / distance metric. On the modelling front, we use an Ordinary Least Squares (OLS) estimator for the gravity model, while we employ a Generalized Method of Moments and Instrumental Variable (GMM / IV) estimator for the spatial models in order to obtain unbiased and consistent parameter estimates. We evaluate various goodness-of-fit measures and in-sample predictions by comparing them among each other as well as to those of a state-of-the practice transport model (as provided by national spatial planning bureau (NPVM)). This comparison allows us to draw solid conclusions with respect to the suitability of the presented method for predicting commuting flows.

2. Case study

2.1 Set up

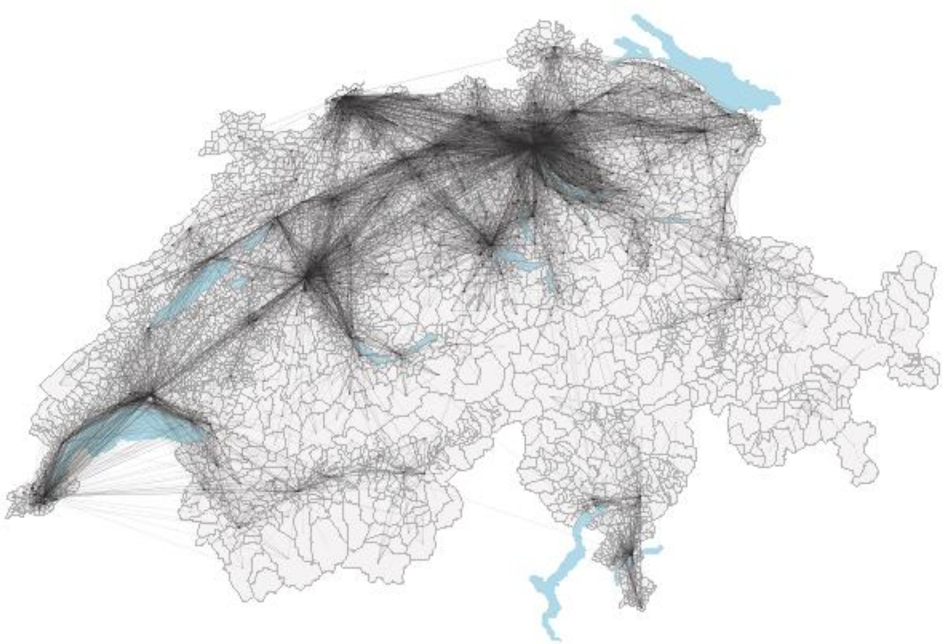
In brief, we designed a case study for public transport commuting flows in Switzerland to illustrate the concept of OD flow modelling, based on travel-to-work trip data from the Federal Census of 2000. The data cover 2896 Swiss municipalities and contain over 250’000 observations in their initial form. However, the given data set does not fill the whole flow matrix that contains 2896^2 = 8,386,816 flows. The flows represent entries in the OD flow matrix T (see Table 2), where columns reflect origins and rows destinations)[1]. For the remaining OD pairs we assume zero-valued travel flows. An important aspect is the issue with how to deal with zero flows. A large fraction of zero-valued OD flows would definitely point towards a Poisson or a (zero-inflated) negative Binomial interaction model. However, neither a Poisson nor a negative Binomial spatial autoregressive regression model for OD flows has been developed so far. We include income differences between Swiss communes as an explanatory variable in our models, since a higher income gives incentives to commute. In conclusion, we filter the initial flow matrix for inter-communal travel trips, income data available only in 1595 communes and all zero flows, which gives a final sample size of 46,659 OD flows[2]. Clearly, this is a limitation of our modelling approach. Nevertheless, the findings can be of apparent value for pointing directions.

2.2 The Swiss network

A presentation of the resulting commuting flows is given in Figure 1, where higher flow values correspond to a thicker representation of the linkages and only flows bigger than the median are showed. This figure clearly shows dense linear features emanating among larger cities in Switzerland, which also hints at the monocentric nature of employment in the area of big cities and towns.

[1] Note that initially every municipality resembles an origin and a destination.
[2] Due to filtering, a municipality does not have to be an origin and a destination anymore.

Figure 1: Map of filtered public transportation commuting flows within Switzerland in 2000. Flows emanate from the centroid of each municipality.

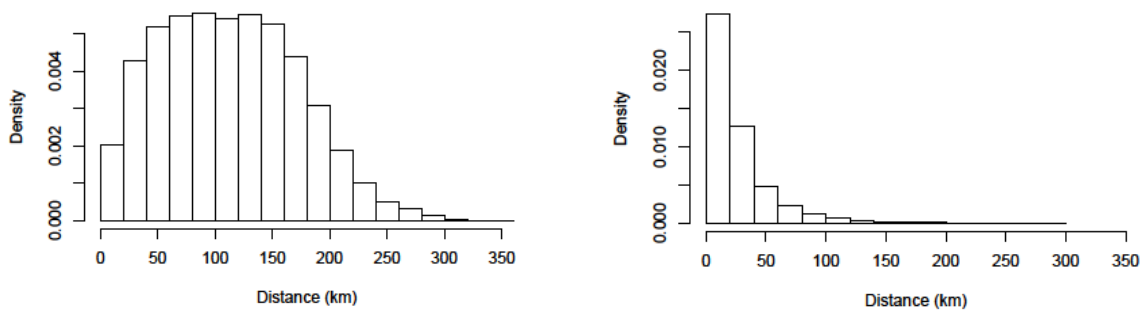


Examining travel-to-work distances within the public transportation flow network reveals that even after filtering for zero flows the distribution of distances is heavily right skewed. Apparently, low flows in the initial data set get filtered leading to higher median values for flows in the first five deciles, which again shows the importance of the bigger cities in Switzerland. Note that for the left boxplot, all zero flows were transformed with $y_{new} = y + 1$.

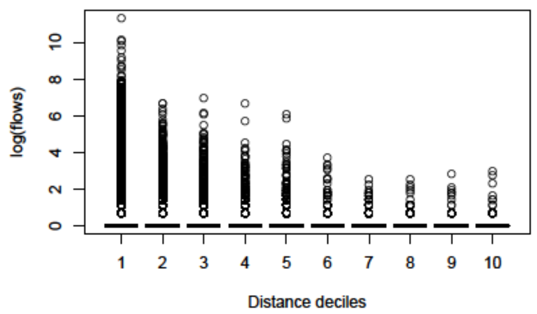
Figure 2: Distributions of network distances and flows (in logs) before (left) and after filtering (right) in deciles.

(a) Distance distribution before filtering

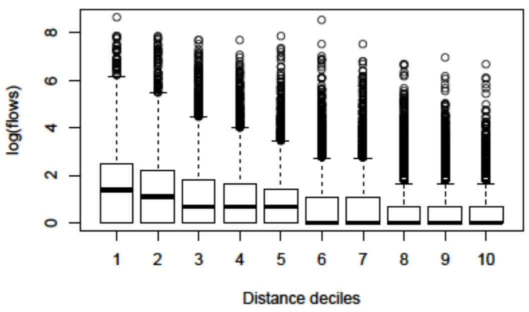
(b) Distance distribution after filtering



c) Flow distribution before filtering



(d) Flow distribution after filtering



2.3 The model variables

Modelling commuting behaviour requires a set of relevant explanatory variables that capture the origin's and destinations' characteristics, along with the mechanisms that generate the trips among them. The dependent variable, inter-communal travel flows, is regressed on several independent variables obtained or derived from the 2000 Federal Census, the Swiss national transport model ARE (2005), and the Institute for Transport Planning and Systems (IVT) of ETH Zurich. We use the following variables in our framework, which are also common in explaining public transport demand in the literature (e.g. LeSage and Thomas-Agnan, 2015; Farmer, 2011; Axhausen et al., 2015).

Table 1: Model variables and their summary statistics

Statistic	**Definition**	**Mean**	**Std. Dev**	**Min**	**Max**
Flow	Av. daily flows	11.1	79.1	1	5,698
Network dist.	minutes	74.1	42.8	5.8	730.3
Income diff. rel	in percent	0.068	0.235	-0.643	1.744
Population (o)	# inhabitants	13,661.970	40,809.420	45	363,273
Jobs (d)	# jobs	19,918.660	55,560.380	11	341,213
Pop. density (d)	# pop. / area (in km^2)	1,372.3	1,719.4	1.5	9,581.1
Job density (o)	# jobs / area (in km^2)	657.9	1,856.8	1	67,561.3
Pop. accessibility (d)	# accessible pop.	277,352.7	224,990.9	93.8	1,064.884
Job accessibility (o)	# accessible jobs	120,298.3	107,246.1	35.3	567,509.4
Car (o)	# cars / pop.	0.5	0.085	0	1.177
Car (d)	# cars / pop.	0.5	0.089	0	1.177
Jobs3rd (o)	# jobs in 3rd sector / # jobs	0.595	0.176	0.044	1
Jobs3rd (d)	# jobs in 3rd sector / # jobs	0.652	0.174	0.044	0.990
Workers (o)	# workers3 / pop.	0.524	0.036	0.277	0.726
Workers (d)	# workers3 / pop.	0.524	0.036	0.277	0.726
Note:	(o),(d) = at origin, at destination municipalities N = 46,659				

Network distance is reported as travel time in minutes between municipalities. It basically resembles a generalised cost of travelling with public transport and incorporates not only the raw travel time, but also the waiting time at stations and the number of transfers on travel-to-work trips. Hence, network distance reflects the structure of public transportation in a spatial grid and should influence the dependent variable negatively. Income is an important variable for transport demand as the difference of income between destinations and origins can be seen as a reason to commute[3]. In general, one would expect that income differences have positive influence on flows. The question that arises about the influence of income is whether it has a direct impact or not. To start, we assume that income directly influences commuting flows, thus is exogenous without any other confounding effects. Job and population accessibility by public transportation are measures of available job positions and population

[3] Refer to Sarlas et al. (2015) for the derivation of the income per commune.

in surrounding municipalities of origins and destinations. They are constructed as follows (Sarlas 2015)[4]:

$$Job\ accessibility_i = \sum_{i}^{j} Jobs_j * exp\left(\beta cost_{ij}^{\alpha}\right)$$

$$Population\ accessibility_i = \sum_{i}^{j} Population_j * exp\left(\beta cost_{ij}^{\alpha}\right)$$

Because they should capture how municipalities generally compete against each other in terms of available population and jobs, both measures should have a negative impact on the flow under consideration, either at an origin or destination level. The total number of jobs, the jobs in the service sector, along with population and economically active population should be positively correlated with flows. Subsequently, the area variable is used to calculate job and population density variables, while their influence on flows is not clear a priori. Last, car ownership per commune reflects people's mode choice shares and should therefore have a negative impact on public transportation flows, as it is assumed that private and public transport are competing[5].

2.4 Origin-Destination flows and the Gravity model

OD flow modelling aims at explaining variation in the levels of flows between the n^2 OD pairs based on a sample containing n spatial units (LeSage and Pace, 2008). An important difference to classic interaction modelling arises in how a flow matrix (see Table 2) translates into an n^2 vector of flows, which defines the OD model structure (see Table 3). We stick to an origin-centric ordering in this paper. In Table 3, the first n elements in the stacked flow vector indicate flows from origin 1 to all n destinations. The last n elements of this vector represent flows from origin n to destinations 1 to n.

Table 2: OD matrix

T	o_1	o_2	…	o_n
d_1	$o_1 \to d_1$	$o_2 \to d_1$	…	$o_n \to d_1$
d_2	$o_1 \to d_2$	$o_2 \to d_2$	…	$o_n \to d_2$
⋮	⋮	⋮		⋮
d_n	$o_1 \to d_n$	$o_2 \to d_n$	…	$o_n \to d_n$

Table 3: OD vector I^o (first column)

I^o	o^o	d^o
	1	1
⋮	⋮	⋮
n	1	n
⋮	⋮	⋮
n^2-n+1	n	1
⋮	⋮	⋮
n^2	n	n

The starting point is a logged least-squares gravity model for OD flows in the form of

$$\log(y) = \alpha \log(l_N) + \beta_o \log(X_o) + \beta_d \log(X_d) + \delta \left(\frac{inc_d - inc_o}{inc_o}\right) + \gamma \log(g) + \epsilon,$$

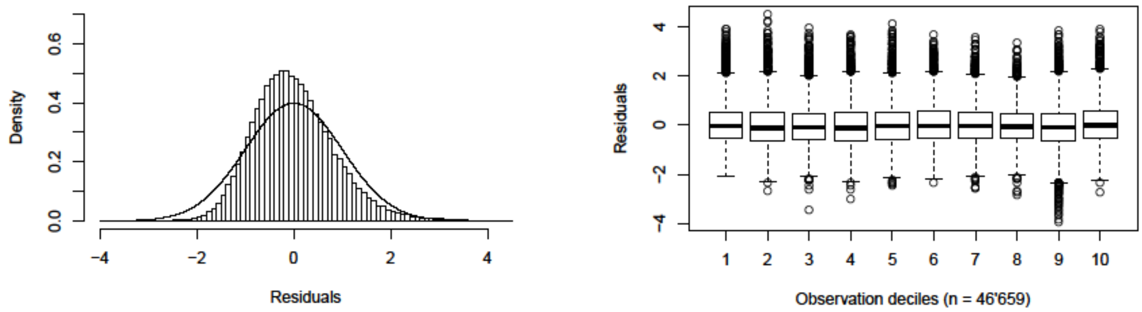
[4] Note that the parameters of the distance decay functions are taken from Sarlas and Axhausen (2015).
[5] Commuters using a mix of private and public transportation are not considered.

where X_o and X_d are characteristics of origins and destinations, g denotes the network distance and $((inc_d - inc_o)/inc_o)$ reflects the relative difference of income between destination and origin municipalities.

Estimation results of the gravity model are shown in Table 4. The associated adjusted R-squared of 51.8% shows that a bit more than half of the variation in the commuting flows can be explained by the OLS model. The residuals of the gravity model are almost normally distributed, yet they exhibit a slightly right skewed distribution and feature a higher kurtosis (see Fig. 3). Furthermore, heteroskedasticity robust standard errors are calculated and presented to account for potential non-constant variance in the residuals. We checked the variance inflation factors, which are not shown here, for all independent variables and found no multi-collinearity issues.

Figure 3: Gravity model diagnostics

(a) Distribution of the model residuals (b) Boxplot of the model residuals



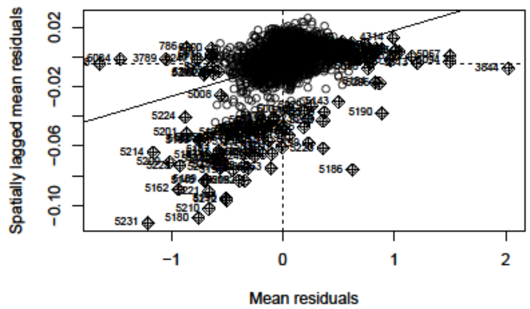
All parameters are highly significant except those of the share of 3rd sector jobs at origins and the share of cars per origin municipality having p-values lower than 5% and 1% respectively. The network distance decay parameter (-1.537) is within the expected range for commuting patterns and in accordance with previous studies. All other explanatory variables have a much weaker impact on the dependent variable, but this finding is in line with the expectations of existing literature (LeSage and Thomas-Agnan, 2015; Farmer, 2011). Income differences between destinations and origins have a significant and positive effect on travel-to-work trips and should be interpreted as an elasticity, since relative differences are used. This intuitively makes sense, as a higher income in another commune gives incentive to commute. Among the destination characteristics, an increase in the share of workers (economically active population per municipality) and the number of jobs yield the biggest influence on travel-to-work trips (0.665 and 0.473), whereas an increase in the accessibility of people in neighbouring communes has the strongest negative influence on commuting (-0.176). A higher accessibility of population by public transport results in less transport demand in the destination of the OD flow under consideration and thus can be interpreted as a kind of competition variable. Regarding the origin-specific variables, the parameters for population and the share of workers show the strongest positive impact (0.365 and 0.440) on commuting flows. An increase in both variables is positively related to travel demand, leading to higher flows away from origin communes. If more jobs in the neighbouring communes are available by means of public transportation, this has a negative, and again big effect on travel-to-work trips. Interestingly, a higher number of jobs in the origin itself has a smaller effect on commuting flows compared to more available jobs outside of it. As expected, cars have negative impact since it captures, at least partially, the competition with public transportation.

2.5 Spatial dependence in the residuals

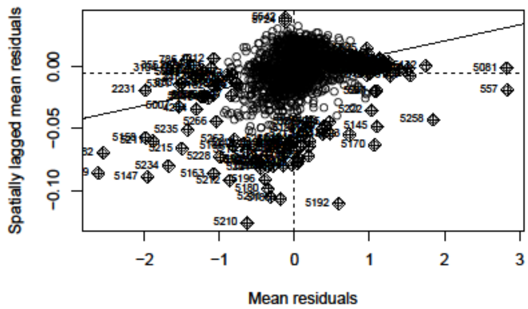
OLS relies on independent observations. In the context of OD commuting flows this assumes that the use of a network distance variable should eradicate the spatial dependence among the sample OD pairs, which is likely not the case in this setting, as Griffith and Jones (1980, p. 190) state that "flows associated with a destination are “enhanced or diminished in accordance with the propensity of attractiveness of its neighboring destination locations". The same holds for flows from origins. Hence, residuals of gravity models indicate the presence of untreated spatial effects (Curry, 1972). By applying Moran’s I tests (Moran, 1948), which in our setting weight the mean residuals by network- and economic distance, we find that they indeed exhibit remaining spatial dependence and thus justify the need for spatial models. That is, the mean residuals of either origins or destinations are positively correlated with its spatially lagged disturbances. Furthermore, squares in the Moran scatterplots (see Figure 4) reveal influential observations (communes) which are able to influence the slope (global Moran's I) unproportionally. Interestingly, a spatial analysis as such does not reveal any clear pattern or cluster in Switzerland, even though it was quite similar for both origins and destinations. In addition, for the case of origins, the spatial autocorrelation is significant up to a radius of 120 minutes of travel time whereas for destinations it is up to 100 minutes.

Figure 4: Spatial dependence in the mean OLS residuals with a network distance (first row) and economic distance (second row) based spatial weight matrix

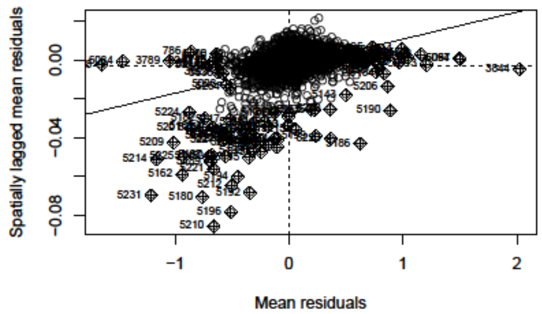
(a) Moran’s I plot for origins, MI: 0.097



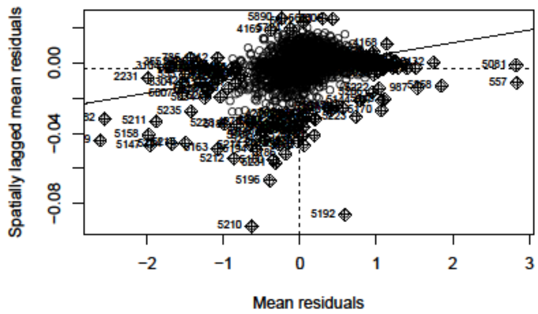
(b) Moran’s I plot for destinations, MI: 0.066



(c) Moran’s I plot for origins, MI: 0.082



(d) Moran’s I plot for destinations, MI: 0.053



2.6 The spatial autoregressive model

Spatial autoregressive models (SAR) in log form are typically written as

$$log(y) = \alpha \log(l_N) + \rho_i W_i \log(y) + \beta_o log(X_o) + \beta_d log(X_d) + \delta\,(\text{inc.}) + \gamma \log(g) + \epsilon, \qquad with\ i = o, d, b,$$

where in our case the weights for the weight matrix W_i are defined as

$$Netw.dist.weights:\quad w_{ij} = \frac{1}{travel\ time_{ij}},\quad Econ.dist.weights:\quad w_{ij} = \left(\frac{travel\ time_{ij}}{\exp((inc_d - inc_o)/inc_o)}\right)^{-1}$$

For economic distance weights, travel times are weighted with the exponential of relative differences in communal incomes. For example: A positive difference resulting from a higher income in destinations than origins for a given OD-dyad lowers travel times, implying a higher weight overall because of taking the inverse. Note that as a result of \cref{sec: acasestudyforswitzerland-spatialdependenceinresiduals} network and economic distances higher than a certain threshold are set to zero, thereby assuming that there is no more remaining spatial autocorrelation after it from origins and/or destinations. 120 minutes of travelling away from origins and 100 minutes away from destinations are set as thresholds. Furthermore, a minmax-standardisation routine is applied to all weights, basically to account for the size of spatial units and to prevent the modifiable area unit problem (Kelejian and Prucha, 2010, Killer, 2014).

These weights are now assigned to neighbouring origins of an OD pair in the case of an origin-centric weight matrix, essentially weighting the corresponding commuting flows from neighbours of an origin to a specific destination. The same principle holds for the case of destination-centric spatial weight matrices. A third weight matrix sums the origin- and destination based weight matrix and accounts for both effects.

We use the Lagrange multiplier test for spatial dependence applied to the OLS gravity model residuals in combination with all weighting schemes. The tests indicate that spatial autoregressive models with spatial autoregressive error terms (SAC) yield the highest statistics for network and economic distance weighting. Spatial error models rank second whereas spatial lag/autoregressive models are those with the lowest test statistics. Because of computer memory issues, which is well known and stated problem (LeSage and Pace, 2008), we could only estimate spatial lag models using the sphet package in R (Piras, 2010).

As it can be seen in Table 4, SAR models relying on origin- and destination-centric network and economic distance weights show positive influence of neighbouring communes on travel-to-work trips. Rho is higher than 1, which is an artefact of using the minmax approach for the spatial weights when building W_i, i = (o,d,b) instead of classic row-normalization (Kelejian and Prucha, 2010). Compared to row-normalization, where a different normalization factor for the elements of each row is used, the minmax approach also considers column sums and applies a single one for the whole matrix. In the transition from the gravity model to the SAR models, variables Car (o), Car (d), and Jobs3rd (o) are not statistically significant anymore and the impact of network distance becomes smaller. Interestingly, rho for the SAR model relying on economic distance weights has a bigger impact compared to the network distance weighted SAR. We want to emphasize that parameter estimates of spatial autoregressive regression models cannot be interpreted as simple elasticities as in the gravity model, since spatial spillovers complicate the task of interpreting estimates from these models in a direct way. Furthermore, the spatial models yield a higher goodness-of-fit measure than the gravity model. Note that pseudo R^2 values must be treated with caution, as they are not equivalent to OLS-based R^2 measures.

Table 4: Gravity model and spatial autoregressive models estimates

	Dependent variable: log(commuting flows)					
	Gravity model (OLS)		**SAR (GMM / 2IV)**		**SAR (GMM / 2IV)**	
			Network distance weights		*Econ. distance weights*	
	Estimate	Sign.	Estimate	Sign.	Estimate	Sign.
(Intercept)	4.443	***	5.765	***	5.788	***
log(Netw. distance)	-1.537	***	-1.250	***	-1.254	***
Rel. Income diff.	0.085	***	0.047	**	0.041	**
log(Jobs) (d)	0.473	***	0.307	***	0.308	***
log(Pop. density) (d)	0.030	***	0.036	***	0.036	***
log(Pop. access.) (d)	-0.176	***	-0.207	***	-0.206	***
log(Jobs3rd) (d)	0.102	***	0.082	***	0.082	***
log(Car) (d)	-0.071	***	-0.007		-0.006	
log(Workers) (d)	0.665	***	0.409	***	0.417	***
log(Population) (o)	0.440	***	0.359	***	0.358	***
log(Job density) (o)	-0.043	***	-0.042	***	-0.042	***
log(Job access.) (o)	-0.180	***	-0.239	***	-0.239	***
log(Jobs3rd) (o)	-0.027	**	-0.019		-0.018	
log(Car) (o)	-0.023	*	-0.003		-0.002	
log(Workers) (o)	0.365	***	0.249	***	0.254	***
rho			2.387	***	2.704	***
R^2	0.5177					
Pseudo adj. R^2			0.5898		0.5893	
HC robust std. errors	yes		yes		yes	
Note:					* p < 0.1; ** p < 0.05; *** p < 0.01	

The resulting in-sample predictions of the spatial models outperform those from the current NPVM for different accuracy measures, as can be seen in Table 5[6]. The considered measures are: Root mean/median squared percentage error (RMSPE / RMdSPE), mean/median absolute percentage error (MAPE / MdAPE) and symmetric mean/median absolute percentage error (SMAPE / SMdAPE). Percentage errors have the advantage of being scale-independent and are frequently used to compare prediction performance across different models. The MAPE and MdAPE have the disadvantage that they put a heavier penalty on negative errors than on positive errors. This observation led to the use of the so-called “symmetric” measures (Makridakis, 1993): SMAPE, SMdAPE. RMS(P)E is often preferred to the MSE as it is on the same scale as the data. Measures based on median values are more robust to outliers and therefore smaller than those based on mean values. Apparently, the OLS gravity model prediction errors are the biggest ones among all models. The spatial models perform best without doubt. It seems that they are less sensitive to outliers due to a significantly smaller variation over all measures and only slightly bigger measures based on mean percentage errors.

Table 5: In-sample predictions

	RMSPE	RMdSPE	MAPE	MdAPE	SMAPE	SMdAPE
NPVM	87.50	6.49	271.76	64.92	74.12	64.24
Gravity model (OLS)	131.20	68.76	913.60	687.62	143.36	154.94
SAR (GMM / 2IV); Network. dist. weigths	6.81	4.75	51.53	47.52	62.59	55.22
SAR (GMM / 2IV); Economic. dist. weigths	6.40	5.13	51.99	51.34	68.96	63.03

2.7 Endogeneity in the gravity model

The problem of endogeneity is severe for any model if it exists. It results in biased and inconsistent estimates, making parameter estimates and inference invalid. In this framework, the mean income as an economic characteristic of origins/destinations and as part of the spatial weight matrix is used to explain variation in commuting flows. Due to the economic nature of income it may as well be that there is an omitted variable bias, causing the disturbances to be correlated with the regressor in the case of the OLS gravity model. Even worse in SAR models, where the regressor and spatially weighted dependent variable are both correlated with the error terms. This fact violates the conditional mean assumption which essentially means that is not possible to fully distinguish the influence of and between each variable in the model.

To account for endogeneity in the gravity model we employ an Instrumental variable (IV) approach in order to get a consistent, but biased, and less efficient estimator (compared to OLS). In general, instruments provide a solution for threats to internal validity that cause a non-zero expected conditional error term. Methodologically, the estimation of the model takes place in two stages: A first step to isolate the uncorrelated part of the explanatory variable(s) with the disturbances. In the second step the predictions from the first step are used in the original causal relationship. Both stages use OLS, but despite the name, estimation is done in a single step in order to get right standard errors. The most difficult part is basically finding valid instruments, satisfying two conditions: Instrument relevance and exogeneity.

As stated before, it is difficult to think of income to be exogenous in the case of commuting. First and foremost, there may be other (omitted) variables explaining variation in travel-to-work trips that are correlated with income - taxes at municipality level for example. Second, it is difficult to assume no interaction with other variables in the model. In general terms, because of strong interrelations of transportation, human settlement, urban agglomeration and economic activities concentrated in cities, the gravity model should be tested for endogeneity since income is used as a variable. Usually, family background, workforce variables or characteristics of job positions are used when it comes to find instruments for income. Sarlas et al. (2015) found evidence for the positive impact of the latter on mean salaries. The variables that are chosen as instruments are given in Table 6. Generally, two groups of instruments can be distinguished: Instrumental variables 1-4 reflect sector specific attributes of jobs while the latter ones relate to required skills. All above listed IV’s are included in the 2SLS regression framework.

[6] See Sarlas and Axhausen (2015) for a definition of the accuracy measures.

In order to have a valid IV model according to existing theory, three tests are considered. The rejection of the F-test on the instruments in the first stage reveals that there are actually no weak instruments, i.e. no weak first stage-relationship. The Wu-Hausmann test examines the consistency of the OLS estimates under the assumption that IV is consistent. Due to its rejection OLS indeed is inconsistent, suggesting that endogeneity is present. The last test is called Sargan or J-test and tests instrument exogeneity using overidentifying restrictions. Since it is not rejected we can conclude that the chosen instruments are valid.

Table 6: Gravity model (IV) and instrumental variables

Dependent variable: log(commuting flows)

	Gravity model (IV / 2SLS)		**Instruments**	
	Estimate	Sign.	Name	Description
(Intercept)	4.452	***	Working 1	Positions in the hotel/restaurant sector
log(Netw. distance)	-1.537	***	Working 2	Positions in the manufact. sector
Rel. Income diff.	0.134	***	Working 3	Positions in the servce sector
log(Jobs) (d)	0.471	***	Working 4	Positions in the private sector
log(Pop. density) (d)	0.028	***	Tertiary education	Positions requiring tert. education
log(Pop. access.) (d)	-0.177	***	Prof. training	Positions requiring prof. training
log(Jobs3rd) (d)	0.103	***	Vocational training	Positions requiring less than voc. train.
log(Car) (d)	-0.071	***	Qualification 1	Positions with highest qualific. demand
log(Workers) (d)	0.669	***	Qualification 2	Positions with professional skills
log(Population) (o)	0.441	***	Management	Positions with no managerial duties
log(Job density) (o)	-0.041	***		
log(Job access.) (o)	-0.178	***		
log(Jobs3rd) (o)	-0.028	**		
log(Car) (o)	-0.023	*		
log(Workers) (o)	0.363	***		
			IV diagnostic tests	
R^2	0.5178		Weak instruments	1286.218 ***
Pseudo adj. R^2			Wu-Hausmann	4.751 *
HC robust std. errors	yes		Sargan	18.293
Note:				* p < 0.1; ** p < 0.05; *** p < 0.01

The estimation results concerning the variables reveal almost the same values compared to the OLS gravity model. Just the estimate of relative income difference has probably changed the most in the IV framework, yielding stronger and positive impact on commuting flows (0.134 versus 0.085). The model fit statistic has not changed (substantially) compared to the R-squared of the OLS model.

2.8 Endogeneity in spatial models

In this paper we don't present further calculations regarding the endogeneity problem described before. Clearly, this issue affects spatial models in an even more complex way than gravity models, since we do not only include an endogenous regressor, but also endogenous weight matrices. Thus, the spatial model estimates in Table 4 are biased and inconsistent. In this section we therefore present a brief summary for a recipe to treat for endogeneity according to Drukker et al. (2013).

The presented IV gravity model now acts as a kind of basis in order to calculate the corrected relative income difference variable estimate spatial autoregressive models. Since we have found valid instruments for the income difference between origin and destination municipalities, it is now possible to use the predicted and thus corrected income values (see the first equation below) of the first stage in IV for constructing the spatial weights.

$$\left(\frac{\widehat{inc_d - inc_o}}{inc_o}\right) = all\ instruments + all\ exogenous\ variables + \ \varepsilon$$

$$Econ.dist.weights: \quad w_{ij} = \left(\frac{travel\ time_{ij}}{\exp((\widehat{inc_d - inc_o})/inc_o)}\right)^{-1}$$

By directly including predicted values of income in the construction of the spatial weight matrix, we can account for previously endogenous elements. Drukker’s 4-step estimation method (Drukker et al., 2013) can be then used to get consistent coefficients. An implementation in R (sphet package) is available.

3. Conclusion

In this paper we implemented a direct transport demand model for OD public transport commuting flows in Switzerland. It is based on data from the Federal Census of 2000, the Lohnstrukturerhebung 2000 and the National Transport Model 2000. Further variables are based on calculations by the Institute for Transport Planning and Systems of ETH Zurich.
Methodologically, we employed a three step process to examine the problem of spatial dependence in OD commuting flows when network and economic distance are used as underlying impedance function. The starting point was a simple OLS gravity model relying on independent observations, which we then replaced by spatial autoregressive models that are based on two weighting schemes (network and economic distance) in order to account for untreated spatial dependence in the residuals of the OLS gravity model. We used an origin- and destination-centric weight matrix to account for both origin and destination effects. In the last step we checked if endogeneity is present in the OLS gravity model by applying an IV regression approach using valid instruments for relative income differences. Furthermore we presented a way to treat for endogenous regressors and weight matrices in spatial models.
We applied a filter method due to a large fraction of zero-valued flows and income data available for only 1595 communes, which gave a final sample of 46,659 observations. The estimates of the OLS gravity model were in line with expectations of existing literature concerning its statistical and economical importance. Four Moran’s I tests showed that the gravity model's residuals contain patterns of remaining autocorrelation up to a radius of 120 minutes of travel time. Lagrange multiplier tests indicated to estimate spatial autoregressive models with spatial error terms, but due to computer memory issues we could only calculate spatial autoregressive/lag models where we used network and economic distance weighting schemes. We were able to show that neighbouring communes have a positive influence on OD commuting flows under consideration. This finding supports the lower coefficients for network distance in the spatial models compared to the aspatial gravity model. The impact of relative income differences were found to be lower in both spatial models and slightly less statistically significant. The remaining explanatory variables remained stable across all models in sign and magnitude, except for car ownership and jobs in the service sector being insignificant in the spatial models. Last, we showed that the relative income difference variable indeed is endogenous using a valid set of instruments.

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