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ABSTRACT

In order to mitigate climate change, several countries around the world have introduced or are planning a CO_2 tax on energy consumption. The effectiveness of such a tax depends on the level of the short- and long-run price elasticity. Moreover, acceptance of a CO2 tax by a society depends on both the distributional effects of such a tax among households and its spatial effects among regions.

In this paper, the regional impact of a hypothetical CO_2 tax on gasoline consumption in Switzerland is analysed by estimating a demand function for gasoline using panel data from 547 Swiss municipalities from 2001 to 2008. Gasoline sales were collected from the five largest gasoline companies operating in Switzerland, covering about 60% of overall sales. Swiss municipalities are relatively small units, and car ownership and use in one municipality is thought to influence gasoline sales in the neighbouring ones. Accordingly, the method used in the model also accounts for spatial correlation in the consumption of gasoline.

Overall, our spatial econometric analysis shows that the tax burden of a CO2 tax will be higher in rural areas than in urban areas.

JEL: D, D2, Q, Q4, R2

Keywords: gasoline demand, aggregate panel data, spatial economic effect, spatial econometrics.

1 Introduction

In order to mitigate climate change, several countries around the world have introduced or are planning a CO_2 tax on energy consumption. The effectiveness of such a tax depends on the level of the short- and long-run price elasticity. Moreover, the acceptance of a CO_2 tax by a society depends on both the distributional effects of such a tax among households and its spatial effects among regions. The literature analysing the distributional effects of such a tax on households is relatively large. Bento et al. (2009) analysed distributional effects of fuel taxes for the United States, and Sterner (2012) analysed distributional impacts of fuel taxes in seven European countries. Dinan and Austin (2002) evaluated the regional effects of an increase in the US federal tax on gasoline that took effect in 1993. They show both that the tax burden among households varies across states and that suburban or rural households are likely to suffer from a higher tax burden since their members tend to drive more than those of urban households. Apart from this study, however, literature on the regional impacts of an increase in the gasoline price or the introduction of an environmental tax is relatively scarce[1].

In 2011, the Swiss Federal Council promoted the adoption of the *Energy Strategy 2050*. The main objective of this strategy is to secure Switzerland's long-run energy supply by promoting the adoption of energy-efficient technologies and the development of renewable energy sources. To implement this strategy, the Swiss Federal Council and the Swiss Federal Office of Energy (SFOE) are planning the introduction of several energy policy measures, such as new standards, subsidies and the introduction of a CO_2 tax for the private transport sector, which accounts for approximately 30% of final consumption. A CO_2 tax on thermal fuels already exists in Switzerland; however, the private transport sector has so far been exempt from paying a similar tax. For this reason, the Swiss parliament recently discussed the introduction of a CO_2 tax on gasoline and diesel of about 20 Swiss franc cents[2] to decrease fuel consumption and , indirectly, promote the adoption of energy-efficient cars.

Analysis of the spatial effects of the introduction of a CO_2 tax is important from both scientific and policy perspectives. The spatial equity effects of a policy measure are particularly relevant in a federal state such as Switzerland, where solidarity across cantons is an important principle. Moreover, policymakers are also interested in the impact of a CO_2 tax on the traditional gasoline tax revenues collected by the central government.

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1 For instance, Egger (2005) applied spatial GMM estimation methods to a panel data set to analyse spatial tax competition for goods such as beer, wine, gasoline, and cigarettes among US states from 1975 to 1999. The key findings suggest that neighbouring states respond to regional effects in the tax levels, meaning that they take the tax levels of neighbouring states into account.

2 A 20 Swiss franc cents CO_2 tax per litre of gasoline would correspond to a carbon tax of approx. 86 Swiss francs per ton of CO_2 emitted. In Switzerland, policy measurements related to the consumption of diesel are of secondary interest: The share of the vehicle fleet running on diesel accounted for approx. 20% of the whole fleet on average during the past decade, at least in residential mobility.

For instance, between 2000 and 2010, the petroleum tax revenues to the state amounted on average to some 4.0-5.0 bn Swiss Francs per year, which represented almost 9% of the Swiss Federal budget.

The goals of this paper are to estimate price and income elasticities for Swiss residential gasoline demand by considering spatial effects. Additionally, we analyse the impact of the introduction of a CO_2 tax on gasoline consumption in Swiss municipalities. We are particularly interested in estimating the effects at municipality level of the spatial spillovers arising from the change in price level. In order to do this, we apply a spatial autoregressive model with autoregressive disturbances (SARAR) to a panel data set that considers 547 municipalities for the period 2001 to 2008. We decided to concentrate the analysis on gasoline demand because the share of diesel consumption in Switzerland is small.

In this paper, we argue that spatial spillover effects in gasoline consumption make it important to use a spatial econometric approach in our empirical analysis. Further, the use of spatial econometric models allows the effect of a change in an independent variable across the regions to be divided into a direct effect and an indirect effect (spatial spillovers). Spatial spillovers and spatial clusters in gasoline consumption are determined by the socioeconomic relations between cross-sectional units such as municipalities. For instance, gasoline consumption in one region can be influenced by the lifestyle choices of households in neighbouring municipalities, such as a trend towards buying new energy-efficient cars. This behaviour can create spatial clusters in the adoption and use of cars and, therefore, in gasoline consumption. Another spatial economic effect may arise from workers living in one municipality or country but working in adjacent or nearby municipalities or countries[3]. Finally, the fact that Swiss municipalities are very small geographical units reinforces the hypothesis that the consumption of gasoline in a municipality is not only a function of explanatory variables in this municipality but also subject to spatial spillovers from traffic.

As mentioned above, empirical studies have generally neglected the presence of possible spatial effects in gasoline consumption. However, a relatively high number of studies on estimating gasoline demand have been published[4]. Many of these estimations use aggregate regional panel data sets and both static and dynamic specifications of the gasoline demand model[5]. Baltagi and Griffin (1984) state that models which account for the stock of cars consider it as quasi-fixed, so such a model cannot account for long-run responses such as replacement of vehicles. Such models result in a price elasticity which captures the changes in fuel consumption caused by all effects, such as using the vehicle stock less or renewing it. The dilemma is that vehicle characteristics are an important determinant of fuel consumption, but using these characteristics as explanatory factors in estimating long-run effects is cumbersome, as also stated by Basso and Oum (2007).

[3] See LeSage and Pace (2009) for a detailed overview on the different types of spatial effects (spillovers).

[4] For a systematic review of these papers see the meta-analysis of Brons et al. (2006). This author reports a mean value of some -0.3 to -0.45 for the price elasticity of gasoline.

[5] See Dahl (2012) for a more detailed review of gasoline demand studies.

Pock (2010) used data for 14 European countries over the period 1990-2004 to estimate a dynamic model specification for gasoline. Pock's main assertion is that many previous studies may suffer from a bias in estimated income and price elasticities of gasoline demand due to the omission of diesel powered cars or lack of distinction between gasoline- and diesel-powered cars. However, in such partial adjustment models, the inclusion of the capital stock is not completely correct, because these models have been introduced to estimate short- and long-run elasticities in a situation where the capital stock is not observed. Clearly, the demand for fuel depends on the average efficiency of the vehicle fleet and its usage.

Most of the studies discussed in Dahl (2012) do not use a spatial econometric approach and provide an estimation of the price and income elasticities that does not vary across regions. One exception is the study by Pirotte and Madre (2011), who use a spatial lag model without considering the spatial error effect and a spatial error model without considering the spatial lag in the dependent variable. These authors used a panel data set of 21 French regions over 17 years to analyse elasticities of car traffic. They argue that traffic (and therefore fuel quantity consumed, since the dependent variable is constructed with the fuel quantity consumed) in a region is a matter of spatial dependence, since traffic and therefore consumption is not tied to a certain place. The neglect of spatial correlation in the model specification may either lead to biased coefficient estimates, if spatial correlation is present in the dependent variable, or to misleading inference, if spatial correlation is present in the residuals, or to both. The study identifies positive and significant spatial correlation in both the residuals and the dependent variable. However, this study did not estimate a spatial econometric model that considers spatial correlation in the dependent variable as well as in the residuals. As we will discuss later, the econometric approach used in this study considers both types of correlation simultaneously.

The evidence on gasoline demand for Switzerland is fairly limited. Wasserfallen and Güntensberger (1988) used time-series data from 1962-85 to estimate price and income elasticities of gasoline consumption, indicating that the price elasticity of Swiss gasoline demand is equal to -0.30 and the income elasticity is equal to 0.5. Schleiniger (1995) used time-series data and an error correction model for the period 1967-1994 and found a short-run price elasticity of -0.24. An interesting study using panel data was authored by Banfi et al. (2005). They analysed gasoline tourism in the Swiss border regions for the period of 1985-1997. A panel data model was estimated for three border regions, namely for those adjacent to Italy, France and Germany. They used sales from approximately 190 Swiss fuel stations located within 5 km of the border, implicitly assuming that after 5 km from the border, no gasoline tourism takes place. The estimated elasticity with respect to the Swiss gasoline price was found to be relatively high at -1.75, showing that gasoline sales, at least in border regions, are relatively sensitive to price changes. Accordingly, the main reason for this high price elasticity arises from the fact that the demand analysed was in the Swiss border regions. Switzerland exhibits a strong price differential across its borders, inducing foreign car owners to fuel their cars on the Swiss side of the border. The strength of this inducement also responds to the Swiss gasoline price. Finally, Baranzini et al. (2013) analysed long- and short-run price and income elasticities using time-series cointegrating techniques to estimate a log-linear demand function for Swiss gasoline demand per capita. They found a long-run price elasticity of gasoline demand of -0.34 and one of -0.1 for the short-run.

The present paper will improve some shortcomings of the studies discussed above, such as small data sets, omission of the stock of cars and disregard of spatial correlation in the model specification or in an econometric approach which considers spatial correlation in the dependent variable and in the residuals simultaneously. Moreover, we propose the estimation of both a short-run and a long-run gasoline demand model. According to our best knowledge, this is one of the first studies which estimates a gasoline demand function using a panel data set combined with a spatial econometric approach.

The paper proceeds as follows. Section 2 derives an appropriate model for residential gasoline demand using household production theory. From this, a spatial econometric model is specified. The next step provides descriptive statistics of the variables used in the econometric model. Section 3 shortly summarises the appropriate econometric procedures for the estimation of a gasoline demand function using panel data, and the estimation results of both non-spatial and spatial versions of the econometric model are provided. Using a counterfactual simulation, the short- and long-run effects of an increase in the Swiss gasoline price of 0.20 CHF (the size of the proposed CO_2 tax) on Swiss gasoline demand, governmental tax revenues, and GHG emissions from gasoline consumption are described in Section 4. Section 5 concludes.

2 Model Specification and Data

Following Banfi et al. (2005), we decided to apply the household production theory to the analysis of energy consumption to specify the empirical gasoline demand model, that is, to identify the explanatory variables to be considered in the analysis. In this theoretical framework, the demand for gasoline is modeled as a demand for an energy service[6].

If we assume that a household obtains utility from purchased market goods and from private transport services, which are produced with two inputs, gasoline and cars, and that in the short run the number of cars cannot be changed, a utility function can be written as

$$U = U(S(G, \overline{CS}), X, D, R) \ , \tag{1}$$

where S is the transport service and G denotes the quantity of gasoline consumed. $\overline{CS}$ is the (fix) capital stock (stock of cars), X is a composite good representing a commodity basket that the household consumes at unit price, and D and R represent demographic and geographic characteristics, which in turn determine the household's preferences. Following Deaton and Muellbauer (1980), the household's decision process can be modeled as a two-stage optimisation problem. In the first stage, the household minimises its variable costs accruing from the production of any arbitrary amount of S. In the second stage, the household maximises utility from consumption of the energy service and other goods subject to its budget constraint. For the model specification in this empirical analysis, we just consider the first stage, which is represented with the following equations:

$$\begin{aligned} &\underset{G,C}{\text{Min}} \ (P_G \cdot G + P_{CS} \cdot \overline{CS}) \\ &\text{subject to} \\ &S = \hat{S}(G, \overline{CS}) \end{aligned} \tag{2}$$

The result of this optimisation problem is the variable cost function

$$VC = VC(P_G, \overline{CS}, \hat{S}) \ . \tag{3}$$

If we consider a long-run situation in which the households can change the number of cars, the result of the optimization problem is the following total cost function

[6] A detailed explanation of the household production theory can be found in Deaton and Muellbauer (1980). Further, we are well aware of different possibilities besides this to explain gasoline demand at the household level. For instance, Baltagi and Griffin (1984) specified individual gasoline demand to be the product of number of kilometres driven per car and the gasoline consumption of the average car per kilometre driven (i.e. efficiency) times the total number of cars. Accordingly, the three main factors then are the degree of car utilisation, the efficiency of the car stock and the absolute level of the car stock. However, the first two factors are not observable when using municipality data for Switzerland.

$$TC = TC(P_G, P_C, \hat{S}). \tag{4}$$

From these cost functions, the short- and long-run demand functions can be derived by differentiating equations (3) or (4) with respect to the factor price P_G. For the short-run, we obtain

$$G^* = E^*(P_G, \overline{CS}, S^*) = G^*(P_G, \overline{CS}, Y, D, G), \tag{5}$$

which depends on the gasoline price P_G, the household's income Y, the stock of cars $\overline{CS}$, and the demographic D and spatial (geographic) characteristics R. The model specification stated by equation (5) assumes that the stock of cars is constant. Therefore, the model represents a short-run gasoline demand specification. To adjust the demand functions stated by equation (5) for the long run, we allow for a situation in which households can also adjust the capital stock (here the stock of cars) to an optimal level given the economic situation.[7] For the long-run, we obtain

$$G^* = E^*(P_G, P_{CS}, S^*) = G^*(P_G, P_{CS}, Y, D, G). \tag{6}$$

We are aware that equation (6) represents a static model in the sense that a change in an explanatory variable would instantaneously lead to an adjustment of the capital stock. Usually, partial adjustment models are used for situations where this would not be the case. However, since one goal of the present article is to estimate a spatial econometric gasoline demand model, we intend to model the long run as previously stated without using a partial adjustment model, since this would imply an additional endogenous variable, lagged consumption, besides the spatially lagged consumption of gasoline.

Based on equations (5) and (6), on previous studies and on availability of the data, we specify the short-run gasoline demand model as

$$G_{it} = f(WG_{it}, PG_{bt}, dist_i, CARSG_{it}, CARSD_{it}, POP_{it}, Y_{it}, Comm_{it}, PUB_i, b_k, c_j), \tag{7}$$

where the index i refers to the municipalities ($i=1..547$), and t is an index for time ($t=1..8$). G_{it} denotes average gasoline demand per gasoline station in a municipality[8]. Unfortunately, we do not have information on the sales of gasoline for all gasoline stations located in a municipality, nor do we have information about the total number of stations in a municipality observable over the sample period. The data set includes information on sales of a sample of

[7] As discussed in Baltagi and Griffin (1984), the results obtained from the estimation of a short-run gasoline demand specification, such as specified by equation (5), with cross-sectional or panel data tend to reflect rather long-run price and income elasticities.

[8] Unlike Banfi et. al (2005), we do not only consider gasoline stations located within five kilometers from the border, but all stations in the cantons from which we were able to collect data. Further, we have a different approach by estimating a gasoline demand function for Switzerland and not only for the border regions. One drawback of the study by Banfi et al. is that the estimated elasticities cannot be generalised for the whole of Switzerland. Most importantly, our data is probably much more accurate, because we have municipality data whereas the study by Banfi et al. used cantonal data.

gasoline stations in a municipality. For this reason, we decided to use the average gasoline sales per station in a municipality as the dependent variable. This average value should represent the gasoline demand for a representative gasoline station of a municipality. For the estimation of the gasoline demand model, we collected data on gasoline station sales from the five largest gasoline retailers in Switzerland. Consequently, we are confident that our average gasoline demand per gasoline station in a municipality is representative of consumption. WG_{it} denotes spatially lagged gasoline demand in the neighbouring municipalities. $\mathbf{W}$ is the spatial weighting matrix, which will be explained below.

It is not a purpose of this article to identify cross-border purchasing activities of Swiss gasoline, but similar to Banfi et al. (2005), we use the distance ($dist$) of the municipality from the border. It is likely that, other factors being equal, gasoline consumption will decrease with increasing distance from the border, since the effect of gasoline tourism is thought to vanish after a certain distance.

In addition, the gasoline demand of households will be affected by the real (CPI adjusted) Swiss gasoline price, the per capita income (Y) in Switzerland, the number of daily commuters from the neighboring countries, Germany, Austria, France and Italy ($Comm$), and, as discussed in the theoretical model, the stock of diesel- and gasoline-powered cars ($CARSD$ and $CARSG$). We expect a positive influence of the stock of gasoline passenger cars on gasoline consumption and the opposite for the stock of diesel-powered cars in the short run. In addition, it is likely that commuters have an important positive influence on the level of gasoline demand in the border regions, since they travel regularly to Switzerland and can take advantage of the price differential without experiencing additional opportunity costs. Further, we use a variable PUB_i for a proxy of the availability of public transport services in the municipalities, which is the number of bus, tram, and railway stations in a municipality. Unfortunately, this variable was only available for the year 2010 and therefore is time invariant. However, we believe that it should also be representative of the availability of public transport services for our sample period 2001-2008, since it usually takes a long time to substantially expand public transport services. The availability of public transport is expected to have a negative impact on the amount of gasoline consumed in the private mobility sector. b is a dummy variable for the four border regions ($\mathrm{k}=1,2,3,4$) indicating whether a municipality belongs to a canton adjacent to France, Germany, Italy or Austria. Finally, to account for canton-specific effects, we introduce a dummy variable c for each canton, capturing heterogeneity with respect to topological and cultural aspects (j=1,…26).

The long-run gasoline demand model can be specified as

$$G_{it} = f(WG_{it}, PG_{bt}, r_{it}, dist_i, POP_{it}, Y_{it}, Comm_{it}, PUB_i, b_k, c_j) \ ,$$

where r is the interest rate at the cantonal level. This variable should approximate the user cost of cars. In fact, the user cost of a car is composed of two parts, the amortisation and the opportunity cost of capital. Assuming that the selling price of cars is relatively homogeneous across Switzerland, the difference in the user cost of a car is due to difference in the interest rate charged on money borrowed for private purposes.

For the estimation of the gasoline demand function, we use a log-log specification. For the short-run specification, we have

$$\begin{aligned}
\ln(G_{it}) &= \alpha_0 + \lambda\sum_j w_{ij}\ln(G_{it}) + \alpha_1\ln(PG_{bt}) + \alpha_2\ln(CarsG_{it}) + \alpha_3\ln(CarsD_{it}) + \alpha_4\ln(dummy_{it}) + \\
&\quad .\alpha_5\ln\left(\frac{Y_{it}}{POP_{it}}\right) + \alpha_6\ln(dist_i) + \alpha_7\ln(Commu_{it}) + \alpha_8\ln(PUB_i) + \sum_{c=1}^{25}\gamma_c g_c + \sum_{t=2}^{8}\delta_t dt + u_{it} \\
u_{it} &= \rho\cdot\sum_j w_{ij}\cdot u_{jt} + \varepsilon_{it} \\
\varepsilon_{it} &= \mu_i + v_{it}
\end{aligned} \tag{8}$$

and for the long-run we have

$$\begin{aligned}
\ln(G_{it}) &= \alpha_0 + \lambda\sum_j w_{ij}\ln(G_{it}) + \alpha_1\ln(PG_{bt}) + \alpha_4\ln(dummy_{it}) + \alpha_5\ln\left(\frac{Y_{it}}{POP_{it}}\right) + \alpha_6\ln(dist_i) + \\
&\quad .\alpha_7\ln(Commu_{it}) + \alpha_8\ln(PUB_i) + \alpha_9\ln(rate_{jt}) + \sum_{c=1}^{25}\gamma_c g_c + \sum_{t=2}^{8}\delta_t dt + u_{it} \\
u_{it} &= \rho\cdot\sum_j w_{ij}\cdot u_{jt} + \varepsilon_{it} \\
\varepsilon_{it} &= \mu_i + v_{it}
\end{aligned} \tag{9}$$

In addition, as it can be seen from equations (8) and (9), we account for the fact that unobservable variables captured by u_{it} may be spatially correlated as well. As a consequence, standard estimation procedures such as fixed or random effects which do not account for the specific error structure will result in inefficient estimates. The decision to estimate equations (8) and (9) with a spatially lagged dependent variable and spatially lagged residuals (SARAR model) is supported by Lagrange multiplier tests developed by Baltagi et al. (2003 and 2008).

For the estimation technique, we rely on the generalised methods of moments (GMM) estimator as outlined by Kelejian and Prucha (1998) and Kapoor et al. (2007). Prices are treated exogenously, since both producers and consumers are assumed to be price takers.

From the model specified in equation (8), the price elasticity with respect to the Swiss gasoline price (here for the short run) can be calculated as follows:

$$\varepsilon_{PG_{CH,bt}} = \frac{\partial\ln(G_{it})}{\partial\ln(PG_{bt})} = \alpha_1 \ . \tag{10}$$

Taking spatial spillovers in the dependent variable into account, the elasticity described by equation (10) only represents the direct effect on a municipality (see also LeSage (2009) for a detailed overview on spatial effects). If the gasoline price in a municipality changes, this will have a direct effect on gasoline demand in this municipality. When spatial correlation in the dependent variable is taken into account, the change in gasoline demand in this municipality will affect demand in the neighbouring ones. As a result, the initial change in the gasoline price not only has a direct but a total effect on gasoline demand. This can best be seen by solving equation (8) for the dependent variable, which yields

$$
\begin{aligned}
\ln(G_{it}) = \sum_j (\mathbf{I}_{\mathrm{NT}} - \lambda \cdot \mathbf{W} \otimes \mathbf{I}_{\mathrm{T}})^{-1}_{j} \cdot (\alpha_0 + \alpha_1 \ln(PG_{bt}) + \alpha_2 \ln(CarsG_{it}) + \alpha_3 \ln(CarsD_{it}) + \alpha_4 \ln(dummy_{it}) \\
+\alpha_5 \ln\left(\frac{Y_{it}}{POP_{it}}\right) + \alpha_6 \ln(dist_i) + \alpha_7 \ln(Commu_{it}) + \alpha_8 \ln(PUB_i) + \sum_{c=1}^{25} \gamma_c g_c + \sum_{t=2}^{8} \delta_t dt + u_{it})
\end{aligned}
\tag{11}
$$

Accordingly, the (e.g.) price elasticity (here in the short-run) has to be interpreted as total effects which yields

$$
\varepsilon_{PG_{CH,bt}} = \frac{\partial \ln(G_{it})}{\partial \ln(PG_{bt})} = \frac{1}{\mathrm{NT}} \cdot \mathbf{e}_{\mathrm{NT}}{}' \left(\mathbf{I}_{\mathrm{NT}} - \lambda \cdot \mathbf{W} \otimes \mathbf{I}_{\mathrm{T}}\right)^{-1} \cdot \mathbf{e}_{\mathrm{NT}} \cdot (\alpha_1) \tag{12}
$$

and thus every spatial unit, or municipality, is assigned a different elasticity due to the presence of spatial spillovers. Of course, it does not make sense to report elasticities for all municipalities separately; they will be reported as an average for all municipalities. The total effects described in equation (10) will be decomposed into direct effects (as defined by equation (11)) and indirect effects which are equal to the difference between the latter two, see LeSage (2009) for more details.

Table 1 provides descriptive statistics of the variables and data used in the estimation of equations (8) and (9). These descriptive statistics are based on a reduced sample, since in fact some data were missing for some municipalities. The final panel consists of balanced observations on gasoline sales for 547 municipalities over eight years (2001-2008). Of course, we are aware that we are not considering all 2715 Swiss municipalities in our empirical analysis. However, most of the excluded municipalities are very small and do not have a gasoline station. As previously stated, data on Swiss gasoline consumption were collected from the Swiss Oil Association for the five most important gasoline companies located in Switzerland. These companies owned approx. 1,500 out of some 4,200 stations in Switzerland in 2001 and accounted for some 60% of Swiss gasoline sales over the sample period. Further, since one of the five gasoline companies we have in the sample showed a unique sales pattern over the sample period (it is the only company with strongly increasing sales, since it operates small supermarkets at its gasoline stations), we decided to control for the presence of that company in a municipality with a dummy variable (subsequently referred to as 'dummy').

Data on gasoline prices were collected by the Swiss customs authorities and are available on a monthly basis, from which we took yearly averages. The border officers track prices for each border region in Switzerland. Since price data could not be obtained from the oil companies, this was the only remaining source. This explains the considerably low between variation of the price variable in the table below.

Variable	Description	Mean	Stdev. (between)	Stdev. (within)	Stdev. (overall)
G	Gasoline sales per gasoline station in a municipality (1'000 litres)	4'174	6'667	1'173	6'763
PG	Price of Swiss gasoline (Swiss franc cents)	149.8	3.64	16.1	16.5
CARSG	Number of gasoline powered cars	3'820	7'865	601	7'882
CARSD	Number of diesel powered cars	420	854	387	937
POP	Residential population	8'562	20'687	374	20'674
DUMMY	Dummy indicating the presence of a certain gasoline company	0.188	0.376	0.104	0.390
Yp	Swiss per capita income (Swiss francs)	31'368	9'267	2'634	9'268
DIST	Municipality's distance from border (km)	26.5	18.5	0	18.5
COMM	Number of foreign commuters	258	1'571	200	1'582
PUB	Total number of bus-, tram- and railway stations	18	25	0	271
RATE	Real estate interest rates at the cantonal level	3.48%	0.07%	0.4%	0.43%

Table 1: Descriptive statistics of variables used in estimation, N = 547, T=8, averaged by municipality and year

According to LeSage (2009), Elhorst (2010) and Stakhovych and Bijmolt (2009), the researcher defines how the spatial units, here the municipalities, interact with each other through the spatial weighting matrix **W**. The matrix is of size $N \times N$, and an element w_{ij} is greater than zero if spatial unit i interacts with unit j and else zero. Most of all, the diagonal elements of the matrix are zero, and hence a spatial unit is not considered to be a neighbour to itself. Typically, the entries are chosen to be a decreasing function with increasing distance since it is thought that close spatial units affect each other more strongly than distant ones. Most often, these functions are specified to be exponentially or inversely decreasing with increasing distance. One question arising is how to define a concept of "neighbourhood".

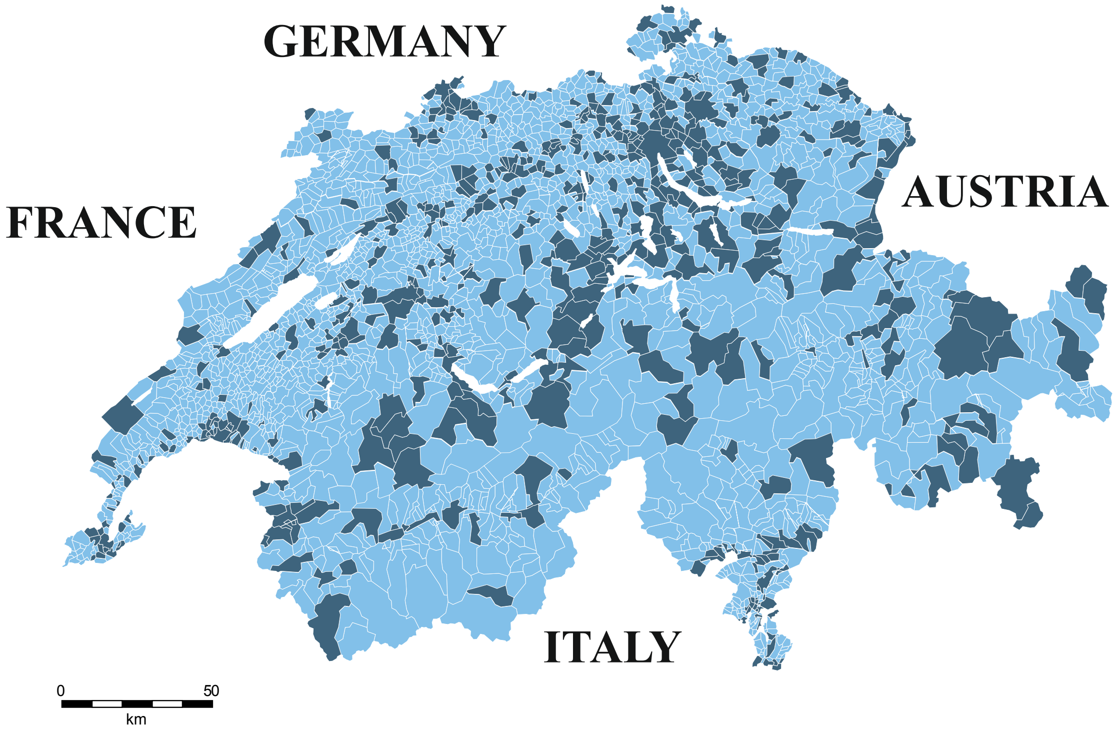

Figure 1: Swiss municipalities with balanced gasoline sales data

Figure 1 shows the Swiss map at the municipal level. The bright blue shaded municipalities denote those with no observation on gasoline sales available. The darker shaded ones denote those for which gasoline sales data were available for the sample period. In most applications, according to LeSage (2009), a contiguity matrix **W** is created such that spatial regions with a common border interact spatially with each other. It can be seen in the figure above that for the present situation this is not a valid option. Generally, it is recommended to consider at least two differently specified weighting matrices to check the robustness of results (Elhorst 2010). For one matrix, we choose a concept of neighbourhood where only the three or five closest municipalities with balanced gasoline sales data affect each other. A more sophisticated approach, however, is to define neighbourhood relations by a Delaunay triangulation algorithm giving the spatial distribution of the municipalities. Roughly speaking, the algorithm relates the closest subset of municipalities to each other when a contiguity criterion cannot be applied using geographic boundaries[9].

We will estimate the spatial econometric model described in equations (8) and (10) using those four different spatial weighting matrices to check the robustness of results: one where the three or five closest municipalities interact spatially with each other, the matrix from the Delaunay algorithm, and a so-called 'sphere-of-influence' matrix which is derived from the triangulation but which uses a threshold distance for spatial interaction. The final choice is in favour of the matrix where spatial correlation is most evident.

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[9] We implemented the algorithm in STATA®, and it is available on request.

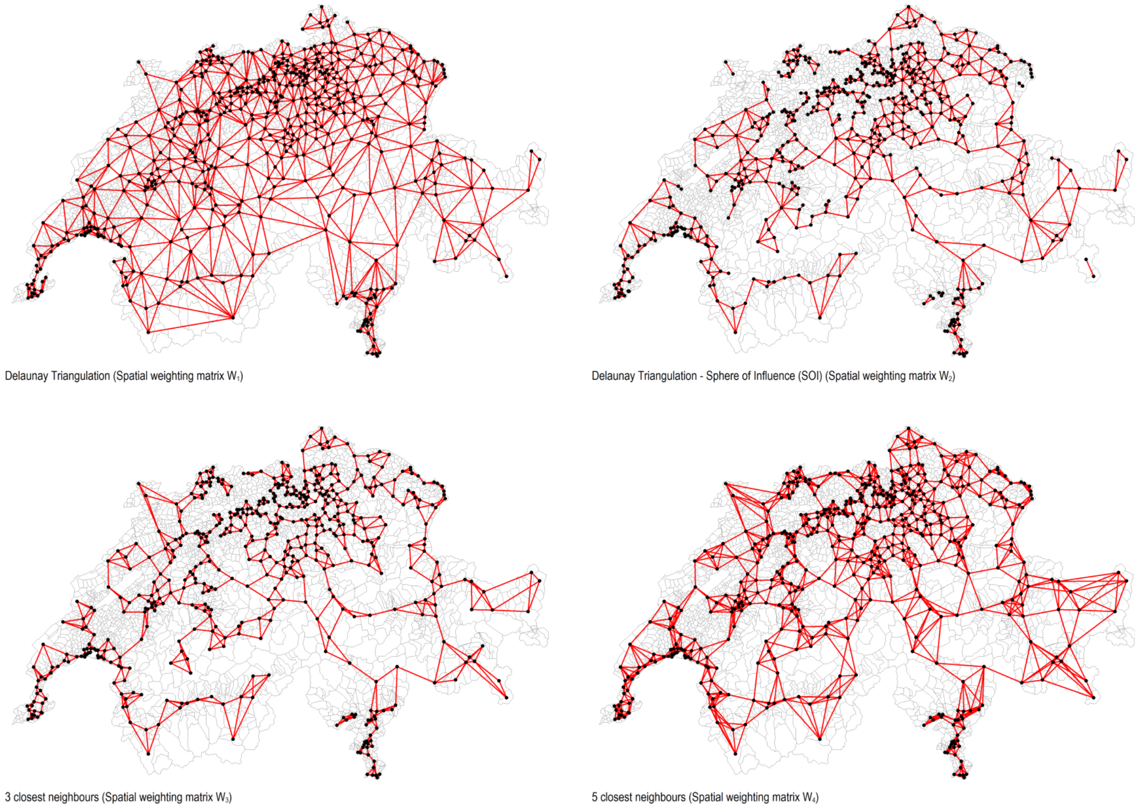

Figure 2: Different spatial weighting matrices to assess spatial dependence in the consumption of Swiss gasoline

3 Econometric Approach and Estimation Results

For the estimation of equations (8) and (9), we decided to use the two classical estimators for panel data, the fixed effects (FE) and the random effects (RE) estimators, as well as a spatial econometric version of these two models, the SARAR models proposed by Kelejian and Prucha (1998) and Kapoor (2007). In the following, we shortly discuss the classical estimation techniques for panel data and then explain the estimators for panel data models used in a spatial econometrics framework.

The main advantage in using panel data estimation techniques such as FE or RE estimators is the ability to control for unobserved heterogeneity. As is well known, the fixed effects estimator allows individual effects to be correlated with exogenous regressors, a situation which is most likely the case in our example. On the other hand, as noted by Baltagi (2005), if this correlation is absent, a random effects estimator is more efficient than the fixed effects estimator. However, the random effects estimator is biased if there is significant correlation between the individual effects and the exogenous regressors. A recent study by Clark and Linzer (2012) points out that researchers should be less concerned with bias than with efficiency, meaning that a bias can be potentially low whereas the gain in efficiency could be dramatic. This fact is likely to be present in our application, since, as is shown in Table 1, most regressors exhibit a far lower within than between variation, a situation in which fixed effects estimators perform badly in terms of efficiency. This fact is also noted in Cameron and Trivedi (2009): under the presence of variables with a low within variation, the FE estimator can produce imprecise coefficients and a low level of efficiency. Further, Clark and Linzer (2012) also show that the results of a Hausman test cannot be equally trusted in a situation where the within variation of regressors is very low. Consequently, we are inclined to use a random effects estimation technique.

We also decided to use a FE and RE version of the SARAR model. This model considers spatial lag dependence (spatial correlation in the dependent variable) and spatial correlation in the error terms in a panel data setting. The proposed method focuses on a generalised methods of moments (GMM) estimator, where it should be said that a maximum likelihood (ML) estimator could also be applied. Actually, most studies use ML estimation techniques and only a few studies have yet applied a GMM estimator to a SARAR model (e.g. Egger et al. 2005; Blàzquez et al. 2013). The general econometric problem is formulated below using matrix notation:

$$
\begin{aligned}
\mathbf{y} &= \lambda \cdot (\mathbf{W} \otimes \mathbf{I}_T)\mathbf{y} + \mathbf{X} \cdot \boldsymbol{\beta} + \mathbf{u} \\
\mathbf{u} &= \rho \cdot (\mathbf{W} \otimes \mathbf{I}_T)\mathbf{u} + \boldsymbol{\varepsilon} \\
\boldsymbol{\varepsilon} &= \boldsymbol{\mu} \otimes \mathbf{e}_T + \boldsymbol{\upsilon}
\end{aligned} \tag{13}
$$

where $\mathbf{y}$ is the NT×1 vector of the dependent variable, N denotes the number of cross-sectional observations, and T the length of the time period. $\mathbf{W}$ is the spatial weighting matrix of dimension N×N, $\mathbf{X}$ is a NT×K matrix of exogenous regressors. The dependent variable vector $\mathbf{y}$ is explained with a spatially lagged vector of the dependent variable $(\mathbf{W} \otimes \mathbf{I}_T)\mathbf{y}$ with scalar coefficient λ and with the matrix of exogenous regressors $\mathbf{X}$ with K×1 coefficient vector $\boldsymbol{\beta}$. Further, the NT×1 vector of residuals $\mathbf{u}$ are spatially correlated with scalar coefficient ρ and NT×1 vector of residuals $\boldsymbol{\varepsilon}$, which is decomposed into a N×1 of time invariant effects $\boldsymbol{\mu}$ and a NT×1 vector of idiosyncratic errors. $\mathbf{I}_T$ is an identity matrix of dimension T×T and $\mathbf{e}_T$ is a T×1 vector of ones. We estimate the model in three steps, as outlined by Kapoor et al. (2007).

Of course, before using spatial econometric methods, it is important to test for the presence of spatial dependence in the data. A simple approach uses the Moran I test, which tests spatial dependence in a cross-sectional model and can be interpreted as the coefficient of an OLS regression of Wy on y. A more sophisticated approach for spatial panel data models was elaborated by Baltagi et al. (2008). Their Lagrangian multiplier test tests jointly for the presence of random effects and spatial correlation in the dependent variable and the respective robust version. This is a test for spatial correlation in the dependent variable in the presence of random effects and a test for random effects in the presence of spatial dependence. It can actually be seen as a modified Breusch and Pagan Lagrangian multiplier test for random effects. According to Baltagi (2003), one also can test for the presence of spatial correlation in the residuals in the possible presence of random effects. We apply these tests to our model described by equation (8). As we discuss later, the results of these tests support the use of a spatial econometric approach. However, for comparison purposes, we decided also to present the results obtained with the classical FE and RE estimators for panel data.

Given this, a non-spatial version of our model is estimated in a first step with a pooled OLS estimator, a FE estimator and RE estimator. We compute an F-test to discriminate FE from OLS, a Breusch Pagan test to discriminate RE from OLS, and a Hausman test to discriminate RE from FE to take the goals of the study into account. Next, the model is extended with a spatially lagged dependent variable and justified with the Moran I test and Baltagi's Lagrange multiplier test for spatial correlation in the dependent variable. Then, the model is augmented with spatial correlation in the residuals.

In the first four columns of Table 2, we tabulate coefficients for non-spatial versions of our demand model, including cantonal dummies. We do not include time dummies in any models. The reasons for not doing so are, first, that they are not significant at the 5% level for both the FE and RE models. Second, since we collected the price data from the Swiss customs authorities, who track the prices in the four border regions (Italy, France, Germany and Austria), the Swiss gasoline price exhibits a very low between variation and almost only consists in within variation, which also can be seen in Table 1. In this situation, the introduction of time dummies or of a time trend tends to increase the standard error of the price coefficient, because the variation over time of the price variable is also captured by the time variables. Moreover, point estimates of our coefficients remain very similar if time dummies are included. We are aware that in one canton we could observe some regional variation of the gasoline price. However, we argue that these variations are relatively small, due to competition among the stations, and constant over time. Therefore, the introduction of cantonal dummies and individual effects should resolve this issue.

Most of the coefficients are significant in the non-spatial models and bear the expected signs. The coefficients obtained from the FE and RE specifications are similar. The F statistic, which tests the hypothesis that all individual effects are jointly equal to zero, is clearly rejected, and hence the fixed effects model has to be preferred over a pooled OLS model. The Breusch and Pagan test for random effects tests whether the variance of the individual effects μ_i is equal to zero. This hypothesis is also strongly rejected, and hence the random effects model also has to be preferred over the pooled OLS model. The Hausman test rejects the hypothesis of no systematic difference in the coefficients obtained by the FE effects model and the RE effects model; the coefficients of the FE model are consistent under the null and under the alternative, whereas the coefficients of the RE model are consistent and efficient under the alternative. As previously discussed and according to Clark and Linzer (2012), applied researchers should be less concerned with a potentially low bias than with precision (variance) of the coefficients and therefore, we prefer the random effects versions of our non-spatial models.

For the non-spatial short-run random effects model in column 2, we obtain a significant price elasticity of -0.275, which is well in line with elasticities reported elsewhere, see for instance Brons et al. (2006). The coefficients of the stock of cars are also significant with the correct sign. In the long-run version of this random effects model in column 4, we disregard the capital stock and use a proxy for the price of capital. As expected, the price elasticity increases significantly to -0.623 for the long run, when the capital stock can be adjusted.

In the second part of Table 2, we report the estimation results obtained using the SARAR model, choosing the W_4 spatial weighting matrix depicted in Figure 2, and with matrix entries that are inversely related to the municipalities' distances between each other. In a preliminary analysis, we estimated several versions of the SARAR model with these variations:

- using the four different spatial weighting matrices W_1-W_4 depicted in Figure 2,
- weighting the distance entries with a function that is inversely or exponentially decreasing with increasing distance,

- neglecting time dummies (or a time trend) or accounting for time dummies (or a time trend), and
- neglecting cantonal dummies or accounting for cantonal dummies.

In general, the results of these specifications confirmed the results in Table 2.

The results obtained with the spatial econometric models are satisfactory. Moreover, the coefficients obtained with the FE and RE estimators are relatively similar. However, for the same reasons mentioned above, we prefer to focus our discussion of the results on the coefficients obtained in the RE setting. Baltagi's robust Lagrange multiplier test for spatial correlation in the dependent variable and the residuals show significance at the 1% level. Therefore, the choice of a SARAR model seems to be justified. In general, neglecting spatial correlation in the error terms leads to inefficient estimates, whereas neglecting spatial correlation in the dependent variable leads to biased coefficient estimates. Therefore, the SARAR model is superior to the other models, and all forthcoming analysis focuses on the results obtained from the SARAR model.

We observe a significant price elasticity of -0.234 in the short run, meaning that a 10% price increase in a municipality will lead to a decrease in the consumption of gasoline in that municipality by 2.34%, ceteris paribus. This value is well in line with earlier literature on gasoline consumption. For the long run, we observe a price elasticity of -0.514, statistically significant at the 1% level and significantly higher that the short-run estimate. The coefficient of the price of capital is positive and significant, which makes sense since capital and energy are substitutes in the long run.

The coefficients of the stocks of both gasoline and diesel powered vehicles are significant and bear the expected sign in the short-run. We do not observe a significant elasticity of Swiss gasoline demand with respect to per capita income in either the short or long run. The coefficient of a municipality's distance from the border is negative and significant as expected, indicating that, ceteris paribus, demand for gasoline is higher close to the border due to foreigners' cross-border purchasing activity as noted by Banfi et al. (2005). In addition, this might be related to the fact that the border cantons are more densely populated and generally show a higher degree of urbanisation.

Finally, we observe a significant and relatively high value of the spatial lag variable of 0.423, indicating that if gasoline consumption (traffic) increases in neighbouring municipalities, ceteris paribus there are spatial spill-over effects to the municipality under consideration of a 4.2% increase in the consumption of gasoline.

		Non-Spatial Models				Spatial Models			
		Short Run		Long Run		Short Run		Long Run	
Coeff.	**Variable**	**FE Model**	**RE Model**	**FE Model**	**RE Model**	**FE Model**	**RE Model**	**FE Model**	**RE Model**
R^2		**0.165**	**0.296**	**0.157**	**0.292**	**0.45**	**0.64**	**0.48**	**0.65**
λ	$W \cdot G_{it}$	-----	-----	-----	-----	0.801 (3.99)***	0.423 (3.93)***	0.840 (3.93)***	0.421 (3.89)***
ρ	$W \cdot u_{it}$	-----	-----	-----	-----	0.460**	0.460**	0.468**	0.468**
α_1	$PG_{CH,bt}$	-0.227 (-3.16)***	-0.275 (-3.85)***	-0.499 (-9.21)***	-0.623 (-12.6)***	-0.175 (-2.15)**	-0.234 (-2.95)***	-0.387 (-5.95)***	-0.514 (-8.87)***
α_2	$CarsG_{it}$	0.099 (2.66)***	0.110 (3.01)***	-----	-----	0.048 (1.24)	0.068 (1.81)*	-----	-----
α_3	$CarsD_{it}$	-0.116 (-6.41)***	-0.130 (-7.63)***	-----	-----	-0.099 (-4.89)***	-0.112 (-5.89)***	-----	-----
α_4	$Dummy_{it}$	0.672 (21.5)***	0.651 (22.6)***	0.665 (21.2)***	0.641 (22.1)***	0.696 (22.0)***	0.661 (23.0)***	0.694 (21.8)***	0.656 (22.8)***
α_5	(Y_{it} / POP_{it})	-0.072 (-1.18)	0.022 (0.39)	-0.155 (-2.57)***	-0.042 (-0.76)	-0.08 (-1.29)	-0.012 (-0.20)	-0.159 (-2.56)***	-0.072 (-1.289
α_6	$dist_i$	-----	-0.097 (-2.779***	-----	-0.100 (-2.87)***	-----	-0.115 (-3.06)***	-----	-0.118 (-3.15)***
α_7	$Commu_{it}$	0.007 (1.57)	0.010 (1.95)*	0.003 (0.63)	0.005 (1.00)	0.008 (1.44)	0.009 (1.719*	0.005 (1.01)	0.005 (1.06)
α_8	PUB_i	-----	-0.139 (4.43)***	-----	-0.132 (-4.20)***	-----	-0.090 (-2.69)***	-----	-0.085 (-2.53)**
α_8	$rate_{jt}$	-----	-----	0.094 (2.88)***	0.111 (3.459***	-----	-----	0.097 (2.59)***	0.109 (2.98)***
F - Test for FE		p = 0.000***		p = 0.000***		p = 0.000***		p = 0.000***	
B&P Test for RE			p = 0.000***		p = 0.000***				
Hausmann Test			p = 0.000***		p = 0.000***		p = 0.0041***		p = 0.002***
Baltagi's cond. LM test for λ						p = 0.0028***	p = 0.0028***	p = 0.0012***	p = 0.0012***
Baltagi's cond LM test for ρ						p = 0.000***	p = 0.000***	p = 0.000***	p = 0.0000*

Table 2: Estimation results for the non-spatial and spatial models in the short and long runs

Note: N = 547, T = 8; T-statistics in parentheses; ***, ** and * indicate 1%, 5% and 10% levels of significance; cantonal dummies are not tabulated.

4 The Impact of a CO_2 tax on the consumption of Swiss gasoline

The results of the spatial econometric model reported in Table 2 can be combined with the spatial weighting matrix to calculate the direct, the indirect, and the total effect of a change in a municipality's explanatory variable. In this paper, we want to quantify the direct and the indirect impact of a change in the Swiss gasoline price determined by the introduction of a CO_2 tax on Swiss gasoline consumption. To perform this analysis, we should first estimate the direct, indirect, and total effects of a change in the general gasoline price variable and then compute the impact of a change in the gasoline price due to the introduction of the CO_2 tax on gasoline demand. Since we are using a log-log functional form, the indirect, direct, and total effects can be interpreted directly as elasticities.

As already indicated by equation (12), our spatial econometric model can be solved for the dependent variable, and by subsequently taking the derivative with respect to the gasoline price, the total average effect[10] of a change in the gasoline price on gasoline demand is obtained by

$$\varepsilon_{PG_{CH,bt}} = \frac{\partial \ln(G_{it})}{\partial \ln(PG_{bt})} \quad = \frac{1}{\mathrm{NT}} \cdot \mathbf{e}_{\mathrm{NT}}{}' \left(\mathbf{I}_{\mathrm{NT}} - \lambda \cdot \mathbf{W} \otimes \mathbf{I}_{\mathrm{T}}\right)^{-1} \cdot \mathbf{e}_{\mathrm{NT}} \cdot (\alpha_1) \quad = \varepsilon_{(\lambda,\alpha)}$$

The difference between the total effect with respect to a change in the Swiss gasoline price and the direct effect, which is represented by the coefficient itself (here α_1), represents the indirect effect of a change in the Swiss gasoline price or, more precisely, the average spillover from a change in a municipality's gasoline price to neighbouring municipalities. Since both λ and α_1 are statistical parameters, we calculate the standard error of the total effects and the indirect effects using the delta method, which is based on the variance-covariance matrix from our coefficient estimates:

$$\mathrm{VAR}\left(\varepsilon_{(\lambda,\alpha)}\right) = \begin{bmatrix} \frac{\partial \varepsilon_{(\lambda,\alpha)}}{\partial \lambda} & \frac{\partial \varepsilon_{(\lambda,\alpha)}}{\partial \alpha} \end{bmatrix} \cdot \begin{bmatrix} \mathrm{VAR}(\lambda) & \mathrm{COV}(\lambda,\alpha) \\ \mathrm{COV}(\lambda,\alpha) & \mathrm{VAR}(\alpha) \end{bmatrix} \cdot \begin{bmatrix} \frac{\partial \varepsilon_{(\lambda,\alpha)}}{\partial \lambda} \\ \frac{\partial \varepsilon_{(\lambda,\alpha)}}{\partial \alpha} \end{bmatrix} \tag{14}$$

where

$$\frac{\partial \varepsilon_{(\lambda,\alpha)}}{\partial \alpha} = \frac{1}{\mathrm{NT}} \cdot \mathbf{e}_{\mathrm{NT}}{}' \left(\mathbf{I}_{\mathrm{NT}} - \lambda \cdot \mathbf{W} \otimes \mathbf{I}_{\mathrm{T}}\right)^{-1} \cdot \mathbf{e}_{\mathrm{NT}}$$

[10] It is an average effect since, due to the spatial structure of the data, all spatial units are subject to other spatial spillovers and therefore are assigned different values of elasticity. Of course, it does not make sense to report all these elasticities but rather to report an average effect.

$$\frac{\partial \varepsilon_{(\lambda,\alpha)}}{\partial \lambda} = \frac{1}{\mathrm{NT}} \cdot \mathbf{e}_{\mathrm{NT}}{}' \left[\mathbf{W} \otimes \mathbf{I}_{\mathrm{T}} \cdot \left(\mathbf{I}_{\mathrm{NT}} - \lambda \cdot \mathbf{W} \otimes \mathbf{I}_{\mathrm{T}} \right)^{-2} \right] \cdot \mathbf{e}_{\mathrm{NT}} \cdot \alpha$$

In Table 3, we report the estimated average total, direct, and indirect effects (elasticities) on gasoline demand induced by a change in the gasoline price.

	Short-Run (RE)			Long-Run (RE)		
Variable	**Av. Tot. Eff.**	**Av. Dir. Eff.**	**Av. Ind. Eff.**	**Av. Tot. Eff.**	**Av. Dir. Eff.**	**Av. Ind. Eff.**
$PG_{CH,bt}$	-0.268***	-0.233***	-0.035***	-0.590***	-0.514***	-0.076***

Table 3: Average total, direct, and indirect effects (elasticities) of the Swiss gasoline price on the demand for Swiss gasoline (***, ** and * denote 1%, 5% and 10% levels of significance respectively and are obtained by the delta method).

Since spatial correlation in the demand for Swiss gasoline is positive, the average total effects are higher in absolute value than the direct effects. The average total effects actually represent the final elasticities of interest and are different for each municipality.

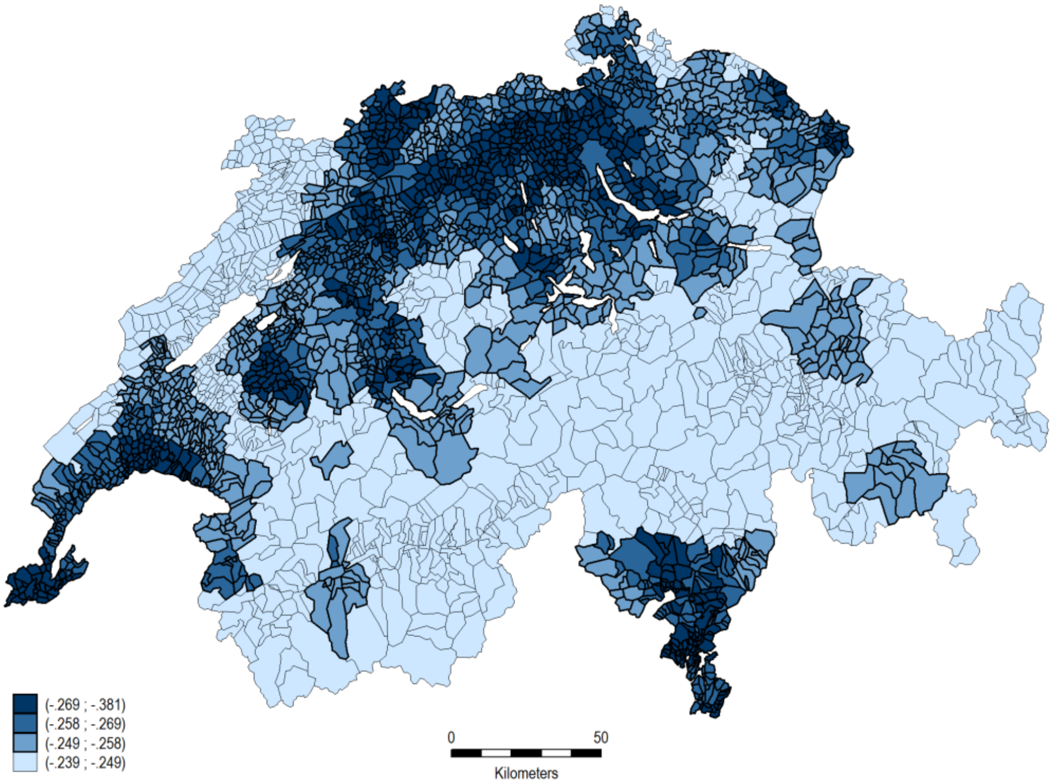

Figure 3: Average total effect (elasticity) of a change in the Swiss gasoline price on Swiss gasoline demand for the short-run

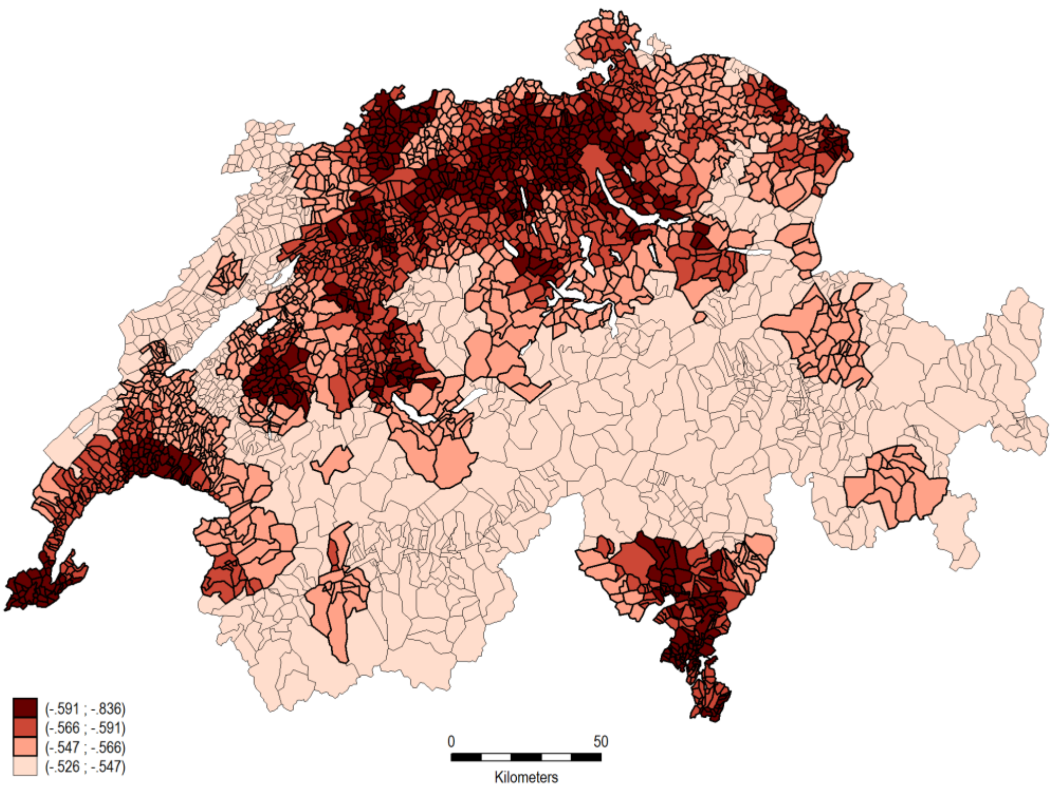

Figure 4: Average total effect (elasticity) of a change in the Swiss gasoline price on Swiss gasoline demand for the long-run

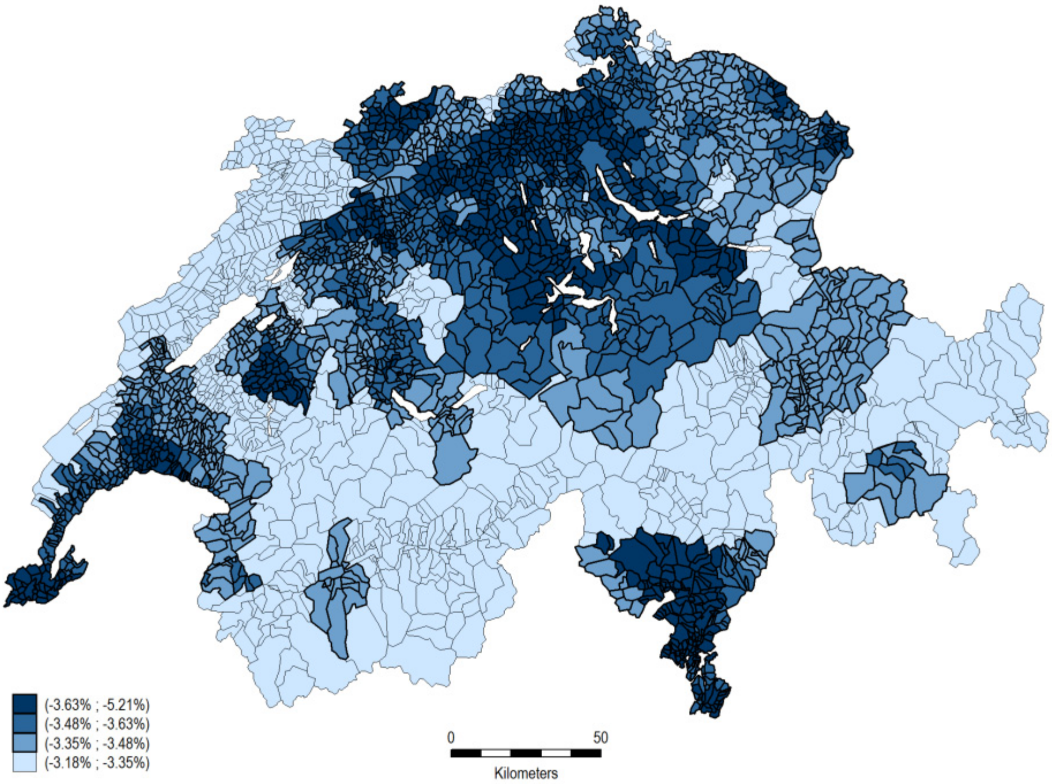

Figure 5: Percentage (total) impacts of a CO_2 tax of 20 Swiss franc cents per litre on gasoline demand for the long-run

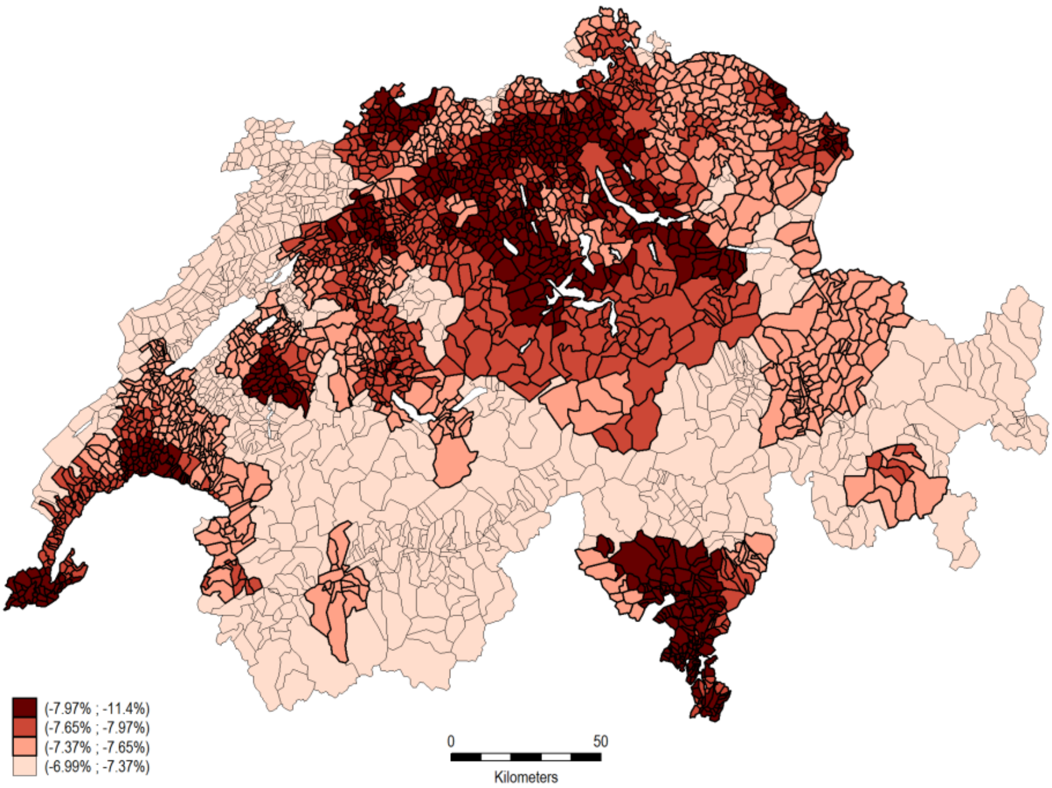

Figure 6: Percentage (total) impacts of a CO_2 tax of 20 Swiss franc cents per litre on gasoline demand for the long-run

The spatial distribution of the total price elasticity is depicted in Figure 3: Average total effect (elasticity) of a change in the Swiss gasoline price on Swiss gasoline demand for the short-run

Figure 4 and Figure 4. Figure 3: Average total effect (elasticity) of a change in the Swiss gasoline price on Swiss gasoline demand for the short-run

Figure 4 and Figure 4 indicate that consumption in the urban or most densely populated regions and the border regions in Switzerland is more sensitive to a change in the Swiss gasoline price. This is in line with our expectations, since in urban regions the supply of public transport services is higher than in rural regions. Therefore, people can change transport mode relatively quickly in urban regions. In line with Banfi et al. (2005), the border regions are affected from gasoline tourism, which leads to higher price sensitivity. In the short run, as illustrated in Figure 3, the computed total elasticities vary from -0.24 to -0.38. For the long run, as shown in Figure 4, we obtain price elasticities ranging from -0.53 to -0.84.

We now want to use the estimated total price elasticities to calculate the spatial impacts of a CO_2 tax. For each year and municipality for which we have data, we artificially increase the Swiss gasoline price by the proposed CO_2 tax of 20 Swiss franc cents per litre. Then we use this price increase to predict the decline in demand, which also will represent losses in taxes to the central government since, as already said, the revenues from the tax itself cannot be accredited to governmental revenues since they are redistributed to the economy. The estimated short- and long-run impacts of a CO_2 tax are illustrated in Table 4.

The proposed tax implies an average increase in the gasoline price of 14%. Given the total short-run price elasticity of -0.268, the tax would decrease demand in the short run by 3.75%. Average yearly consumption of Swiss automotive gasoline over the sample period amounts to 4.5bn litres. Therefore, the tax would lead to a total decline in the demand for Swiss gasoline of some 170 million litres (in the short run). Apart from the CO_2 tax, the Swiss government taxes automotive gasoline with 0.73 Swiss francs per litre on average. Accordingly, the decline in demand will result in a loss of some 125 million Swiss francs per year in the short run.

With the introduction of a CO_2 tax, emissions would decrease by 400,000 tons (one litre of gasoline burned releases some 2.33kg of CO_2). From 2001-2008, Swiss total CO_2 emissions accounted for a yearly average of 45 million tons of CO_2 emitted, where approximately 30% (13.5 million tons) can be attributed to the private mobility sector[11]. Given this, the proposed CO_2 tax would have decreased CO_2 emissions from private mobility by 3.0% over the sample period. According to the Kyoto protocol, Switzerland should reduce its CO_2 emissions by 20% by 2020. The 3.0% calculated here represents a significant contribution to this goal. The parallel calculations for the long run are given in Table 4.

[11] Source Federal Office for the Environment (FOEN) (http://www.bfs.admin.ch/bfs/portal/de/index/themen/21/02/ind32.indicator.72205.3211.html)

For a federal state such as Switzerland, it is important to be aware of the spatial impacts of the introduction of a CO_2 tax. Overall, our spatial econometric analysis shows that the price elasticities among Swiss regions, cantons, and municipalities are quite heterogeneous. Therefore, the tax burden of a CO_2 tax will be relatively heterogeneous among the regions, as can be seen from Figure 5 and Figure 6. Within the federal structure of Switzerland, characterised by a direct democracy system, political discussions are frequently concentrated on socioeconomic disparities among rural, Alpine, and urban regions. Therefore, it would be likely that the introduction of a CO_2 tax could be prevented with a referendum provoked by the different regional impacts. An increase in the public transport services in rural areas could largely harmonise price elasticities and reduce the unequal tax burden across the regions.

	% change in Swiss gasoline price from a 0.20 CHF CO2 tax	**Average total effect on Swiss gasoline consumption**	**Projected decline in the demand for Swiss gasoline (total amount 4.5bn litres)**	**Loss in tax revenues to the state (0.73 CHF per litre9**	**Savings in CO_2 emissions (total and % of 13.5 mn tons of national total)**
Short-Run	14.0%	-3.75%	-170 mn litres	-125 mn CHF	400'000 tons (3.0%)
Long-Run	14.0%	-8.30%	-375 mn litres	-275 mn CHF	875'000 tons (6.5%)

Table 4: Estimated impacts of a CO_2 tax of 0.20 Chf per litre on national gasoline demand, tax revenues to the central government and CO_2 emissions in the short and long runs.

5 Conclusion

Many studies analyse gasoline demand using aggregate panel data, but hardly any of them apply spatial econometric methods. As observed by Pirotte et al. (2011), the main difficulty when explaining gasoline demand or road traffic in small regions using a spatial econometric approach is that the data are only available at the panel unit level, here the municipalities. On the other hand, it is clear that road traffic and hence gasoline demand is not only dependent on a municipality's car fleet or population but also on exchange traffic. Accordingly, the smaller the spatial units are, the stronger is the potential for spatial interaction.

From a methodological perspective, one goal of this paper was to use the GMM estimator developed by Kelejian and Prucha (2007) for the estimations of our demand model. One advantage when using GMM rather than a maximum likelihood approach is that sample size is less of a problem. A second is that there is no need for a distributional assumption about the error terms. Third, the estimation of additional endogenous variables besides the spatially lagged dependent variable is easier when using the GMM approach.

We estimate a spatial lag in Swiss gasoline demand of 0.42 and a spatial error lag of 0.46. This implies that an increase in gasoline consumption by 10% in a municipality spreads to other municipalities and leads to an increase in gasoline consumption of 4.2% (given that the regions are neighbours). We estimate the direct effect of a change in the Swiss gasoline price of -0.23 and a total effect including spatial spillovers of -0.27 in the short run, a value which is well in line with comparable literature. For the long run, we estimate a direct effect of -0.51 and a total effect of -0.57, which is considerably larger than the short-run counterparts, as expected. The long-run response by Swiss car owners to this increase would on average account for a decline in gasoline consumption of 375 million litres and in CO_2 emissions of 875,000 tons. The proposed CO_2 tax can be seen as a steering instrument for influencing final gasoline consumption and for reducing Swiss greenhouse gas emissions from mobility by 6.5%.

For a federal state characterised by direct democracy such as Switzerland, it is always important for policy makers to know the spatial impacts of an energy policy measure. We show that the price elasticity of gasoline demand is quite heterogeneous among the different regions, mostly between rural and urban cantons. In urban areas, the elasticity is generally higher than in rural areas, which may stem from the lower availability of public transport in those areas. This may also mean that the burden of the tax is unequal among the regions, which may lower the political acceptance of the proposed policy.

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