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Spatio-temporal dynamics in Swiss regional unemployment

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Spatio-Temporal Dynamics in Swiss Regional Unemployment*

Rolf Schenker[†], Martin Straub[‡]

February 2011

Abstract

It is generally accepted that regional labor markets are characterized by strong interdependencies. However, only few studies include spatial elements to their estimations. Using the model framework proposed by Cliff and Ord (1973, 1981) and the estimation technique proposed by Kelejian and Prucha (1998), we estimate a spatial time series model for the Swiss cantonal unemployment rates on a quarterly level. Our model contains a spatial lag in the level and in the error term, as well as further exogenous explanatory variables. While both spatial lags turn out to be significant in our estimations, the dependency in the error term seems to be even stronger than the one in the level.

Keywords: Regional Unemployment, Spatial Econometrics, Switzerland
JEL-Classification: C31, C32, E24, R11

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1 Introduction

Until 20 years ago, the Swiss labor market was characterized by very low unemployment rates. Up to the 1980s, Switzerland experienced a permanent state of nearly full employment, but unemployment rates began to rise in the period of economic contraction of 1991/92. After a long time of low variation both over time and across cantons, unemployment rates began to fluctuate as well as to differ between cantons (see, e.g., Feld and Savioz, 2000). This is why the number of studies about this topic has increased notably since 1990.

By now, the body of literature on regional unemployment in Switzerland is quite large (see, e.g., Flückiger et al., 2007a, Steffen, 2005, Parnisari, 2003) and it is a common finding of most studies that the French and Italian speaking cantons of Switzerland are confronted with higher unemployment rates than the German speaking parts (see, e.g., Filippini and Rossi, 1992). However, only a few studies include spatial elements to their estimations, although it is generally accepted that regional labor markets are characterized by strong interdependencies. In this study, we estimate a spatial time series model for the Swiss cantonal unemployment rates on a quarterly level. We determine the variables which explain the levels and fluctuations in the regional unemployment rates and investigate whether these variables retain their explanatory power once spatial elements are added to the model.

In order to incorporate spatial elements into our model, we use the spatial framework proposed by Cliff and Ord (1973, 1981). In this framework, spatial interaction is modeled such that the dependent variable in one regional entity is influenced by a weighted average of the dependent variables in its neighboring entities. This weighted average is constructed using a weighting matrix W which represents the distances between the entities. The analog dependency can be introduced for the model's disturbances. Such models are referred to as spatial autoregressive models and spatial autoregressive error models, respectively. Using both a spatial lag in the dependent variable and in the disturbances, we model the regional unemployment rates in Switzerland between 1998 and 2007. We use the procedure proposed by Kelejian and Prucha (1998) to estimate the model. We find the coefficients of both spatial lags to be significant, with the coefficient of the spatial error lag being higher than the coefficient of the spatial lag in the dependent variable. Moreover, we find the unemployment rate to be increased by the population share of women, the population density, the population share of people aged between 20 and 24 as well as between 25 and 64, the population share of cross-border commuters and the employment share of

the third sector and of modern industries. By contrast, we find decreasing effects on the unemployment rate for the employment share in the public sector. In addition to the mentioned variables, we include national GDP and national wages in the model, allowing for cross-section-specific elasticities.

We contribute to the existing literature in two ways: Firstly, we set up a time series model for the cantonal unemployment rates on a quarterly basis. This allows us to analyze the quarterly regional unemployment rates while most existing studies use annual data or mid-term averages. Secondly, we adapt the Cliff-Ord-framework to the Swiss cantonal unemployment rates. To our knowledge, this framework has not yet been used for the Swiss labor market.

The remainder of the paper is structured as follows: We begin by giving an overview of the existing literature on regional unemployment in Switzerland. Next, we outline the data we use, the structure of our model and the estimation technique. Finally, we discuss the estimation results and summarize our findings in the conclusions.

2 Unemployment Patterns in Switzerland

Until the end of the eighties of the last century, unemployment has not been a very interesting phenomenon in Switzerland, as Feld and Savioz (2000) note. In the seventies, the Swiss labor market was basically characterized by full employment. Even in the severe recession following the first oil price shock, unemployment did not raise notably. This was only possible because the foreign work force was considerably reduced in this period. Even in the eighties, unemployment remained quite low, compared to other European countries.[1]

This situation changed notably in the nineties, when the unemployment rate increased from less than 1% in 1990 to more than 5% in 1997. Together with the strong increase of the national unemployment rate, the disparity of unemployment between the cantons rose considerably. In 1997, the canton of Appenzell Inner Rhodes showed an unemployment rate of 1.9%, while Geneva faced 7.8%. This is quite remarkable given the small size of the country (see Feld and Savioz, 2000).

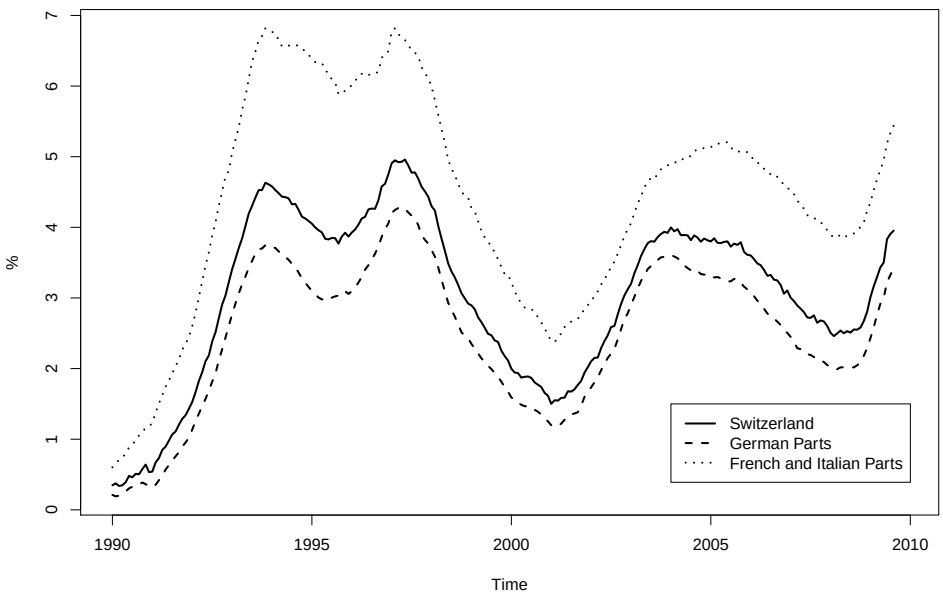
From 1997 to 2000 GDP returned to its growth path and unemployment decreased under 2% again. From 2001 to 2003 Switzerland suffered a period of recession and stag-

[1]The official unemployment rates tend to underestimate the true unemployment, as in this time the unemployment insurance only covered small parts of the economy.

nation that led to an increase of the unemployment rate to more than 4%. From 2003 on, the inverse relationship between GDP growth and the evolution of unemployment seemed to become weaker. A notable GDP growth does not necessarily lead to a decrease of unemployment any more. The strong GDP growth (especially in 2005 – 2007/8) was only followed by a moderate reduction in the unemployment rate. In the same period, Switzerland and the European Union agreed on the free movement of persons. For a discussion of the effects of this agreement on unemployment, see Stalder (2008) and KOF Swiss Economic Institute (2008).

Many studies (see, e.g., Filippini and Rossi, 1992, 1993, Filippini, 1998, Flückiger and Morales, 1998, De Coulon, 1999, Feld and Savioz, 2000, Kleinewefers Lehner, 2001, Flückiger and Vassiliev, 2002, Flückiger et al., 2002, Parnisari, 2003, Steffen, 2005, Flückiger et al., 2007b,a, Brügger et al., 2007) have shown that unemployment is not equally distributed over the Swiss cantons. As can be seen in Figure 1, the unemployment rate in the French and Italian speaking cantons has been permanently higher than in the German cantons since 1990. In some periods, the unemployment rates of Latin cantons are even twice as high as in the German cantons.

Figure 1: *Swiss Unemployment Rate, Total, German- and French/Italian-Speaking Part.*



NOTE: The unemployment rate in the French and Italian speaking cantons has been permanently higher than in the German speaking cantons since 1990.

At first glance, one might think the differences in the unemployment rates to be higher in periods of high unemployment (like around 1995). However, there are different possibilities to measure the disparity of unemployment rates which yield different results. The most commonly used measure is the Gini coefficient (see, e.g., De Coulon, 1999, Parnisari, 2003, Flückiger et al., 2007a). It measures the concentration of unemployment across the cantons. The higher the coefficient, the stronger is the disparity of unemployment in the cantons. The Gini coefficient is plotted together with the Swiss unemployment rate in Figure 2. In periods of high unemployment, the Gini coefficient shows smaller values than in periods of low Swiss unemployment. This means that there is a clear tendency towards an equal distribution in periods of high unemployment.[2]

In contrast, Filippini and Rossi (1992, 1993) observe a rising disparity in periods of high unemployment. These studies analyze the standard deviation of the cantonal unemployment instead of the Gini coefficient. There are two problems with this approach: Firstly, Filippini and Rossi (1992) just compare the values for 1976, 1984 and 1991. Secondly, the standard deviation highly depends on the level. The Gini coefficient also depends on the level, but not as heavily as the standard-deviation: If all data values are doubled, the Gini coefficient remains unchanged while the standard-deviation is doubled as well. When looking at the coefficient of variation, the mean-corrected standard-deviation, (see Figure 3) we see that the variation is smaller in times of high unemployment rates. This is perfectly in line with what we found analyzing the Gini coefficient.

Besides the existence and extent of regional disparities, also the determinants of the cantons' individual levels of unemployment have been analyzed. Starting from the works of Lewin (1983), Filippini and Rossi (1992, 1993) and Projer (1993) many studies about Swiss regional unemployment rates have been published in the last 10 years. While some of them (see, e.g., De Coulon, 1999, Feld and Savioz, 2000) examine regional Beveridge Curves, others look at in- and outflows of unemployment rather than unemployment rates (like Flückiger et al., 2002, Flückiger and Vassiliev, 2002) and estimate duration models.

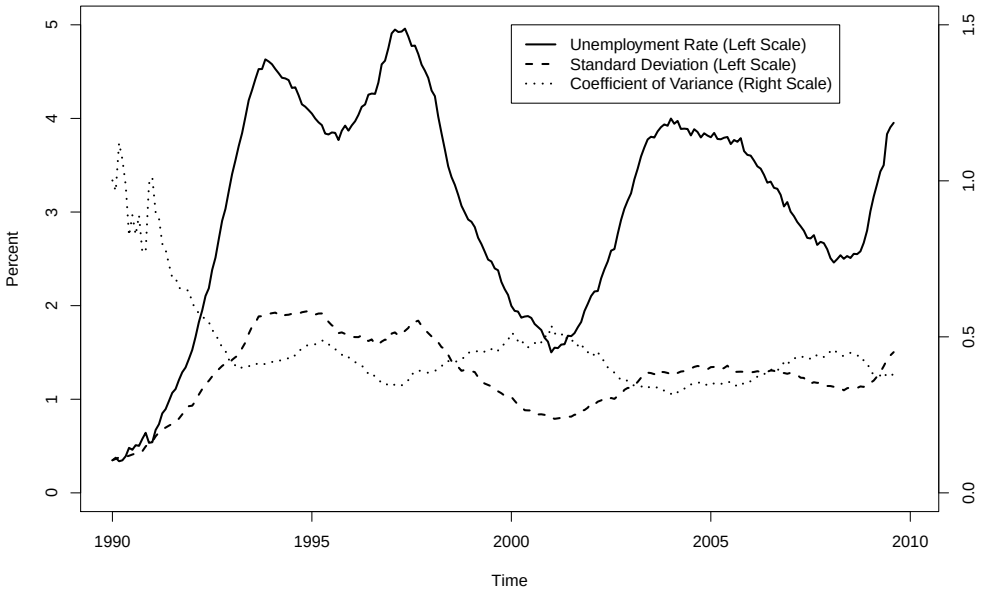
De Coulon (1999) and Flückiger et al. (2002) calculate Beveridge Curves for the Swiss Cantons. Furthermore, De Coulon (1999) analyzes the link between foreign population and regional unemployment and shows that the regional differences in unemployment in Switzerland are higher than in other European countries. The share of foreign residents can partly explain these differences. While, in his estimations, the number of seasonal workers,

[2]The same can be shown using the Theil index instead of the Gini coefficient.

Figure 2: *Swiss Unemployment Rate, Gini Coefficient and Theil Index.*

NOTE: In periods of high unemployment, the Gini coefficient shows smaller values than in periods of low unemployment. This means that there is a clear tendency to an equal distribution in periods of high unemployment.

Figure 3: *Swiss Unemployment Rate, Standard Deviation, and Coefficient of Variation.*



NOTE: The variation is smaller in times of high unemployment. This is perfectly in line with what we found analyzing the Gini coefficient.

cross-border commuters and persons with an annual permit are not able to explain the differences, it's the share of foreigners with a permanent residence permit that helps to explain the regional differences.

Flückiger et al. (2002), Flückiger and Vassiliev (2002) focus on the differences between the Canton of Geneva and the other cantons. They divide the unemployment into structural, frictional and cyclical unemployment. The analysis of micro data enables them to calculate in- and outflows of unemployment. They hence find the smaller outflow from unemployment to be one of the reasons for the higher unemployment rates in Geneva. By estimating duration models, they find the duration of unemployment to be higher in Geneva than in other cantons.

Feld and Savioz (2000) estimate a dynamic panel model. They use a model similar to De Coulon (1999), but add different categories of explanatory variables to it. They criticize that variables related to the cantonal economic policy or the skills of the active population have not been analyzed in Swiss studies. In their estimations, they find high tax burdens and the number of foreign workers to increase cantonal unemployment, while human capital reduces unemployment.

Parnisari (2003) examines the dispersion of unemployment over time. He calculates the Gini coefficient over time and finds the cantonal disparities to augment in times of booms. For the 1980–1990 period, this behavior of cantonal differences is explained by a strong cyclical component and different structural components in the different cantons. For the second phase, 1990–2002, the reason given is the rise of structural unemployment in large parts of the cantons.

Steffen (2005) focuses more on the institutional settings for explaining the differences in the cantonal unemployment rates. She shows that cyclical variables can explain the national level of unemployment, but are not able to explain the different values in the cantons. Political-institutional variables on the other hand can explain the different responses of the cantons to the cyclical framework. Therefore, she concludes that the macroeconomic framework does not have a direct influence on unemployment.

Brügger et al. (2007) examine how unemployment rates behave at borders. They analyze language borders as well as country borders and are thus able to distinguish institutional from cultural differences. Using micro data they are able to estimate entering and quitting probabilities of unemployment. They find differences in the unemployment rate at two types of borders: At the Swiss language borders, the differences are due to

disparities for in- and outflow of unemployed people, while at the national border between Switzerland and Austria, differences occur in the inflows only.

Flückiger et al. (2007a, the extended version of Flückiger et al., 2007b) is a comprehensive study discussing a wide range of approaches and combining macro- and microeconomic approaches. Similar to Parnisari (2003) the authors calculate the Gini coefficient and find cantonal differences to widen in economic boom phases. By calculating in- and outflows as well as duration models, they discover that younger people have a higher probability of becoming unemployed, but their duration in unemployment is shorter, while older people's probability is smaller, but the average duration is longer.

In this article, we assume the unemployment rates of the cantons to be spatially (and temporally) correlated. We investigate which variables determine the cantonal levels of unemployment and whether they also help to explain the differences in the spatial model.

3 The Data

3.1 The Dependent Variable

We analyze the cantonal unemployment rates. However, cantonal borders are not necessarily congruent with the borders of regional labor markets. Cantons as Basel-Stadt and Basel-Land are probably one labor market, as many people working in Basel-Stadt live in Basel-Land. A drawback of this rather politically motivated partitioning is the fact that cantons are often heterogenic entities. The economic, geographic and demographic characteristics can vary notably inside a canton. By analyzing cantons as entities, these variations get lost, leading to a distortion of the estimation results as actually separated labor markets are merged.[3] An important reason in favor of analyzing cantonal data is the fact that the Swiss cantons have relatively large competences in economic and job market policy and thus, the political and institutional environment mainly depends on the cantons. Accordingly, regional data is available for the cantons (the NUTS-3 regions) or groups of cantons ("statistical regions", the NUTS-2 regions). The statistical regions do not have any political autonomy; therefore the analysis of cantonal data is the best choice.

As unemployment rates show strong seasonal characteristics we use the seasonally adjusted series.[4]

[3]For a deeper discussion of this, see Spiezia (2003).

[4]We use an additive X12 procedure with the seasonal filter option X11.

3.2 The Independent Variables

The explanatory variables used in the relevant literature can be parted in four groups. The first group covers information about the population structure; the second group contains variables on the labor force; the third group covers institutional and structural information about the regional entities; the fourth group contains macroeconomic variables.

For the population structure, we include the population density (Feld and Savioz, 2000, Steffen, 2005), variables on the age structure (Elhorst, 2003, Feld and Savioz, 2000) and the share of women (Flückiger et al., 2007a, Filippini, 1998) and foreigners in the population in our model. For the foreigners, different variables have been proposed in the literature, namely the number of persons staying for one year, seasonal workers, foreign resident population and cross-border commuters. All of the mentioned studies use at least one of these categories of foreign workers. Data is available for all these categories, but as we need regional time series, we use the share of cross-border commuters in the working population, as proposed by Flückiger et al. (2007b), Parnisari (2003), Feld and Savioz (2000), Steffen (2005), De Coulon (1999), Flückiger and Vassiliev (2002).

From the second group which contains information about the labor force, we cannot include any variables due to data availability. Variables used in the literature include the share of unemployed persons that are in so called labor market procedures ("arbeitsmarktlichen Massnahmen", Flückiger et al., 2007b), the share of unemployed people that are under sanctions of the unemployment insurance (Flückiger et al., 2007b, Steffen, 2005), the share of unemployed people that are registered (Flückiger et al., 2007b, Parnisari, 2003, De Coulon, 1999), labor market participation (Parnisari, 2003, Elhorst, 2003, Steffen, 2005, De Coulon, 1999, Flückiger and Vassiliev, 2002), the share of part time workers (Steffen, 2005, Flückiger and Vassiliev, 2002) or the share of temporary workers (Parnisari, 2003). All these variables are not available as regional time series and thus not included in this analysis.

Institutional and structural information about the cantons is contained in the third group of variables. We include in this context the employment shares of the three sectors (Steffen, 2005), of the public sector (Steffen, 2005) and of the traditional, modern and high tech industries as well as the dispersion of employment over industries (Elhorst, 2003, Steffen, 2005, Parnisari, 2003, Filippini, 1998). Moreover, we considered the overall tax burden (Feld and Savioz, 2000, Steffen, 2005) but abstained from including it as it did not show significant explanatory power. The literature has furthermore proposed the strength of the unions (Elhorst, 2003, Steffen, 2005) or variables on the regional administration (public

earnings, total expenditures, expenditures for education, expenditures for interests). As there are no sufficiently long and disaggregated time series available for these variables, they are not included in our estimations.

With regard to macroeconomic variables, we use GDP and wages. GDP is an important determinant of unemployment as it measures the overall economy's need for labor. But as regional time series of economic prosperity or income which are usually proposed in the literature (Elhorst, 2003, Feld and Savioz, 2000, Steffen, 2005, Filippini, 1998) are too short, we use the national GDP instead. The wage level represents the price of labor and has been used in many studies (Elhorst, 2003, Steffen, 2005, Filippini, 1998). As there are no cantonal time series on the evolution of wages, we use national time series as well. In turn, we allow the cantons to have individual elasticities to GDP and wages.

3.3 The Weighting Matrix

The weighting matrix W specifies the structure and intensity of the spatial effects. For a set of N regions, it is an $N \times N$ matrix whose diagonal elements are set to zero. Hence, the element w_{ij} represents the intensity of effects between two regions i and j (see, e.g., Anselin and Bera, 1998). The literature knows different approaches for specifying these so called spatial weights. The most frequently used weight specifications are the binary and the distance decay weights.

In the binary weighting matrix, $w_{ij} = 1$ if the regions i and j have a common border, and $w_{ij} = 0$ otherwise (see, e.g., Schanne et al., 2008, Kosfeld and Dreger, 2006). The distance decay function is based on the distance between the centers of the regions and takes the inverse or applies a negative exponential function to it (see, e.g., Schanne et al., 2008, Brügger et al., 2007). Simulation studies by Florax and de Graaff (2004), have shown that a combination of these specifications can be promising: When two regions, i and j have a common border, w_{ij} is the inverse or a negative exponential function of the distance between their capitals, otherwise, $w_{ij} = 0$ (see, e.g., Büttner, 1999, Longhi and Nijkamp, 2007).

However, all these metrics are unable to represent the complex geographic structure of the Swiss cantons. For modeling the relatedness of Swiss cantons and their labor markets, we need more than pure geographical information. Two cantons may be close to each other, but because of geographical obstacles – such as mountains or lakes – their labor markets may be quite separated. This is why the binary and the distance decay specification are not suitable in modeling Swiss cantonal data.

Instead, we use the travel times between the canton's capitals by public transport to construct the W-matrix. We therefore set

$$w_{ij}^* = \frac{1}{tt_{ij}}$$

where tt_{ij} is the travel time from region i's capital to region j's capital. One could argue that the travel times can only be calculated for these specific cities and not for the cantons themselves. Regional capitals can be very far from each other, but due to a large common border, the interaction between the cantons can be quite intensive. We therefore also construct an alternative weighting matrix using all regional capitals and all cities with more than 30'000 inhabitants. The travel times between the cantons is then calculated as weighted means of the travel times of all included cities of the cantons. This alternative W-matrix is then used to check the robustness of our estimation results. The resulting estimation results are very similar to those resulting from the original W-matrix.

To facilitate the interpretation and computation of the spatial autocorrelation, the weighting matrix is row-normalized (see, e.g., Kelejian and Robinson, 1993, Anselin and Rey, 1991):

$$w_{ij} = \frac{w_{ij}^*}{\sum_{j=1}^{N} w_{ij}^*}$$

4 Modeling Regional Unemployment in a Spatial Framework

The standard test for spatial dependency in the literature is the Moran-I Test. However, it is designed for data without a time dimension. We therefore use Lagrange Multiplier (LM) tests as proposed by Burridge (1980) or Anselin (1988). As we are testing for spatial dependency in the endogenous variable as well as in the error term, we perform two separate LM tests. They find our data to show a strong spatial dependence in the levels as well as in the errors (p-values far below 0.1%). We therefore estimate a model with two spatial components: a spatial lag and a spatial error lag, a so-called SARAR(1,1) model.

The explanatory variables consist mostly of regional time series. Additionally, we use national time series for GDP and wages (which are not available on a regional basis in quarterly frequency) and canton-specific constants. N denotes the number of cross-sections, which is 26 in our case as there are 26 cantons in Switzerland. We thus model

the unemployment rate as dependent on its lagged value, the spatial lag and the described set of independent variables.

For each $t \in \mathbf{T}$,

$$y_t = \alpha + \gamma y_{t-1} + A_t\eta + \Delta gdp_{t-1}\theta + \Delta wage_{t-1}\zeta + \rho_1 W y_t + u_t, \qquad |\rho_1| < 1 \quad (4.1)$$

$$u_t = \rho_2 W u_t + \epsilon_t, \qquad |\rho_2| < 1 \quad (4.2)$$

where y_t and y_{t-1} are the $N \times 1$ vectors of unemployment rates in time periods t and $t-1$, respectively, A_t is the $N \times r$ matrix of observations on r exogenous regional time series variables and Δgdp_{t-1} and $\Delta wage_{t-1}$ are the quarter-on-quarter annualized growth rates of seasonally adjusted national real GDP and national nominal wages in time period $t-1$. W is an $N \times N$ spatial weighting matrix of known constants, α is the $N \times 1$ vector of cross-section dummies, η is the $r \times 1$ vector of regression parameters for regional time series variables, θ is the $N \times 1$ vector of GDP elasticities, ζ is the $N \times 1$ vector of wage elasticities, and γ is the temporal autoregressive coefficient. ρ_1 and ρ_2 are scalar spatial autoregressive parameters, u_t is the $N \times 1$ vector of regression disturbances, and ϵ_t is an $N \times 1$ vector of innovations which are assumed to be identically and independently distributed (iid):

$$\epsilon_t \sim iid(0, \sigma_\epsilon^2) \quad (4.3)$$

The variable Wy_t is typically referred to as spatial lag of y_t.

We next define $X_t = (I_N, y_{t-1}, A_t, \Delta gdp_{t-1} I_N, \Delta wage_{t-1} I_N)$ and $\beta = (\alpha', \gamma, \eta', \theta', \zeta')'$, where I_N denotes the identity matrix of dimension N. The model then reads as follows for each time period t:

$$y_t = X_t\beta + \rho_1 W y_t + u_t \quad (4.4)$$

$$u_t = \rho_2 W u_t + \epsilon_t \quad (4.5)$$

X_t has dimension $N \times k$ and β has dimension $k \times 1$, where $k = 3N + r + 1$. We now use stacked matrix notation to write our model in a more compact form, i.e. we stack the cross-section data for all time periods T in matrices or vectors. For example, the $N \times 1$ vectors y_t which contain the cross-sectional data for each time period are stacked into the $NT \times 1$ vector y which contains the cross-sectional data for all time periods. In order to create an $NT \times NT$ matrix containing the W matrix for all time periods, we use the Kronecker product to define $W_{NT} = I_T \otimes W$, where I_T denotes an identity matrix of dimension T.

The model then reads as follows:

$$y = X\beta + \rho_1 W_{NT} y + u \tag{4.6}$$

$$u = \rho_2 W_{NT} u + \epsilon \tag{4.7}$$

Some spatial studies assume that the dependent variable in a cross-section depends on the values of the dependent variable in other cross-sections at time $t-1$ (and not in time t, see, e.g., Giacomini and Granger, 2004). In our model, it is more reasonable to assume that unemployment in one canton depends on unemployment in other cantons at the same time. When unemployment arises from a firm closing in region i, people commuting from other regions get unemployed in the same time period as people living in region i.

Several techniques for estimating models including spatial lags and spatial error lags have been proposed. We use the three-step procedure described by Kelejian and Prucha (1998) as it requires relatively weak assumptions and low computational complexity. Although Kelejian and Prucha presented this model for cross-sectional data, it can easily be adapted for time series (see, e.g., Anselin et al., 2008).

The first estimation step consists of a regression according to equation (4.6). As $W_{NT}y$ is endogenous in this setting, the estimation is performed by two-stage least squares. As instruments, denoted by H, the set $(X, W_{NT}X, W_{NT}^2X)$ is used. This regression produces the estimators $\widetilde{\beta}$ and $\widetilde{\rho_1}$, which are consistent but not efficient, as they do not take into account the dependencies in the errors. The residuals $\widetilde{u}$ are used as estimators for the disturbances u.

In the second step, we use $\tilde{u}$ to estimate the autoregressive parameter ρ_2 by a generalized moments procedure, which is outlined in appendix A.1. The underlying idea is to transform equation (4.7) repeatedly in order to create a system of equations and to use assumption (4.3) to substitute certain terms. By solving the system of equations, the estimators $\widehat{\rho_2}$ and $\widehat{\sigma_\epsilon}$ can be attained.

For the third step, equation (4.6) is premultiplied by $\widehat{\rho_2}W_{NT}$ and then subtracted from its initial version:

$$y - \widehat{\rho_2}W_{NT}y = X\beta - \widehat{\rho_2}W_{NT}X\beta + \rho_1 W_{NT}y - \rho_1\widehat{\rho_2}W_{NT}^2 y + u - \widehat{\rho_2}W_{NT}u \tag{4.8}$$

Setting $y^* = y - \widehat{\rho_2} W_{NT} Y$, $X^* = X - \widehat{\rho_2} W_{NT} X$ and substituting ϵ for $u - \widehat{\rho_2} W_{NT} u$, we get

$$y^* = X^* \beta + \rho_1 W_{NT} y^* + \epsilon \tag{4.9}$$

We now have a model with iid disturbances which we can efficiently estimate by two-stage least squares. The regression produces the final estimators $\widehat{\beta}$ and $\widehat{\rho_1}$.

Kelejian and Prucha (1998) call this step feasible spatial generalized two-stage least squares as the theoretical value of ρ_2, which is needed to calculate y^* and X^*, is not known but estimated.

5 Empirical Application to Swiss Data

This sections presents the estimation results (section 5.1), compares the fit of the spatial model to alternative models (section 5.2) and discusses the spatial dispersion of a shock (section 5.3).

5.1 Estimation Results

In this section, we will present the estimation results and show how they fit into the literature and the relevant theory. The estimation was performed using quarterly data from 1998 to 2007. The detailed estimation results can be found in Table 4 in the appendix. This table contains the results for four alternative models. The "Non-Spatial Model" is the starting point of our analysis as it shows which variables explain the cantonal unemployment rates without the inclusion of spatial elements. The variables showing significance are used in the initial spatial model ("Full Model"). The final spatial model ("Selected Model") results by removing the insignificant variables from the full spatial model. Furthermore, the table shows the estimated parameters of the final spatial model when excluding Basel-Stadt and Geneva from the sample ("Robustness Check").

Non-Spatial Model

The non-spatial model neglects the spatial dependency between the cantons and can thus be estimated by OLS. Nevertheless, the estimated coefficients are quite similar to those of the spatial model. In general, the coefficients are larger than in the spatial model. This is

what we would expect as the information contained in the spatial lag (which has a positive mean) is distributed on the other explanatory variables.

Lags in Space and Time

Most studies about (regional) unemployment include a temporal lag of unemployment to their set of explanatory variables and a small number of studies furthermore includes a spatial lag. According to Elhorst (2003) there is mainly a statistical matter to do so. Usually, unemployment rates are highly correlated across time and space and normally change by relatively small amounts from period to period. As the economic situation in adjacent regions is similar, unemployment rates tend to be correlated in space.

But besides the statistical matter, there is also an economic motivation for including the spatial lag into the estimation system: In a small economy as Switzerland, many employees do not work in the same canton as they live: 57% of the employees do not work in the same community, 12% not in the same canton as they live (results from the population census 2000). When a firm closes, employees from this region, but also from other regions lose their jobs. Furthermore, an unemployed person living in a region also looks for a job in other regions. These two channels cause further spatial interdependencies between the unemployment rates of Swiss cantons. We assume the amount by which the unemployment rate in region i is affected by the unemployment rate in region j to be proportional to the travel times between these two regions and form our W-matrix accordingly.

In our estimations, the coefficients of the temporal and the spatial lags are all highly significant and positive. The coefficient of the temporal lag is 0.81 and the coefficients for the spatial lags in the dependent variable and in the error term are 0.18 and 0.64, respectively. While both spatial lags turn out to be significant, the dependency in the error term seems to be even stronger than the one in the level. This is in line with the finding of Parnisari (2003) stating that spatial correlation is stronger for the cyclical than for the structural component of unemployment.

Women

In their study about Swiss regional unemployment, Flückiger et al. (2007a) find the share of women in the population to be positively correlated with the unemployment rate. Their explanation is that after maternity, women have trouble in getting back to working life and stay unemployed for a longer period than men. Filippini (1998) supposes that another reason for the higher unemployment risk of women lies in the fact that the average

qualification is lower for women than for men. We can see from national statistics that the average educational attainment is indeed lower for women than for men. But as we will see for other variables, we do not have this data for Switzerland on cantonal level and therefore do not include it into our estimations.

In line with to Flückiger et al. (2007a), we find the share of women in the population to increase cantonal unemployment.

Cross-Border Commuters

The expected effect of immigration on regional unemployment is not straightforward, as it can increase both labor supply and demand. The effect on unemployment is zero, if migrants fill vacancies for which no one in the home region is qualified. If migrants fill jobs for which also domestic people are qualified, unemployment increases. The effects on labor demand work indirectly via an increased demand for goods and services.

Cross border commuters come to Switzerland only for work and live abroad. They tend to spend more income in their home regions than in their work regions. Therefore, the effects on labor demand are weaker than for migrants. For migrants, the labor supply side is usually assumed to dominate the labor demand side (see, e.g., Oud et al., 2008). For cross-border commuters the supply side should consequently dominate the demand side even more clearly.

For Switzerland, there are no regional quarterly time series of migration. What we do have at hand are quarterly time series of cross-border commuters on a cantonal level. Cross-border commuters are an important phenomenon in Switzerland. All in all, they only account for about 2% of the working population. But when analyzing cantonal data, we find large variance in the share of cross-border commuters. Not surprisingly, border cantons are confronted with more cross-border commuters, while cantons without borders hardly receive any of them. In Basel-Stadt and Geneva, the number of cross-border commuters accounts for more than 10% (Geneva) or even more than 15% (Basel-Stadt) of the canton's working population. These two cantons are furthermore very small (Basel is the smallest, Geneva the fifth-smallest) and the most urban ones. Their population density is more than 25 (Geneva) and 8 (Basel) times the national population density of Switzerland. This all makes these two cantons particular and different from other cantons. Therefore, Flückiger and Vassiliev (2002) analyze the differences in unemployment in these two cantons compared to the rest of Switzerland. In our model, these two cantons are modeled in the same way as all other cantons; their particularity is mainly captured by their high num-

ber of cross-border commuters and population density. Additionally, we run a robustness check by estimating the model without Basel-Stadt and Geneva.

In a very simple model, Filippini and Rossi (1992) have shown that the number of cross-border commuters has a significant positive effect on the unemployment rate. In a later study, Flückiger et al. (2007b) have concluded that unemployment is higher in border regions. They explain this fact by the higher competition for vacancies in these regions, which decreases the probability to become re-employed and thus increases the unemployment rate. They emphasize that cross-border commuters do not cause unemployment, but make re-entrance to working life more difficult. Of course, this effect does not work in one direction only. The working potential of foreigners increases the labor supply in Swiss border regions. But the labor supply in foreign border regions is also affected by the Swiss working potential. Similarly to the emergence of domestic spatial effects, this leads to an equalization of the unemployment rates in neighboring regions on an international level. As the unemployment rates are generally higher in Switzerland's neighboring regions than in the Swiss border regions, the number of cross-border commuters should increase unemployment in Switzerland.

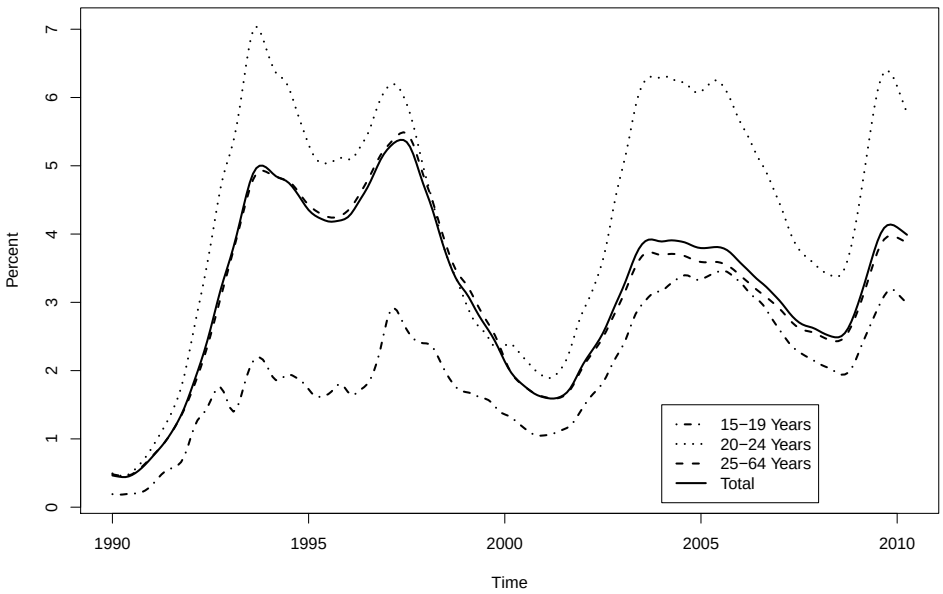
In our estimations we indeed find a positive effect of cross-border commuters on the regional unemployment rates. This is perfectly in line with the above mentioned literature. Furthermore, our robustness check shows that this result is not dominated by Basel-Stadt and Geneva as the coefficient is virtually unchanged when these two cantons are excluded from the sample.

Age Structure

Several studies add variables about the age structure of the population to their set of explanatory variables. Most of them find that regions with a relatively young population are confronted with a more severe unemployment problem than regions with a relatively old population (Hofler and Murphy, 1989, Johnson and Kneebone, 1991, Elhorst, 1995, Molho, 1995a,b, Partridge and Rickman, 1995).

As has been shown by Oud et al. (2008) with German data, changes in the age structure towards a younger population lead to higher, and more persistent unemployment rates. Looking at Spanish data, Lopez-Bazo et al. (2002) find unemployment rates of people aged 16–25 to be notably higher than for the total population. And consequently, the unemployment rates of regions with a large share of people in this cohort tend to be higher.

Figure 4: *Swiss Unemployment Rates in Different Age Cohorts.*



NOTE: From 1990 to 2004, the unemployment rate of the cohort 15–19 years has always been lower than for any other cohort. On the other hand, the unemployment rate of the 20–24 years old people was higher than in the other cohorts.

For Switzerland, things are different. From 1990 to 2004, the unemployment rate of the cohort 15–19 years has always been lower than for any other cohort (see Figure 4). Compared to other countries, the unemployment rate for this cohort is very low. In the European Union, unemployment among young people is measured in the cohort until 25 years and is thus not entirely comparable to Switzerland. Due to the different systems of industrial training in the different countries, it is furthermore difficult to find the correct age categories for comparison. Nonetheless, it can be said that in the European Union unemployment among young people is much higher than for total population. In the last years, the unemployment rate of people below 25 years was twice the rate for the total population and usually between 15% and 20% (cf. Eurostat, 2009).[5]

[5]In Germany and Austria – where roughly comparable industrial training programs exist – the differences between the age categories were not as high, while in France and Italy this ratio was even larger than 2.

In their study about Switzerland, Flückiger and Vassiliev (2002) have shown that the probability of losing the job is higher for younger people compared to the total population. On the other hand, the average duration of unemployment is much shorter for younger people.

As we would expect from the above argumentation, Feld and Savioz (2000) showed that the higher the number of young people in a canton, the lower is unemployment. They suppose that this could be a human capital effect.

We include the share of people in the following age categories into our estimations: 20–24 years and 25–64 years. The base line category is therefore people aged under 20 years and people aged over 64 years. The shares of 20–24 years and 25–64 years old people both have a significant positive effect on regional unemployment. We see two reasons for the fact that both coefficients are positive: firstly, with the exception of the 15–19 years old people, the former two age categories cover those people who are actually able to register as unemployed. Thus, it makes sense that a higher population share of these cohorts should in principle increase the unemployment rate. Secondly, we already mentioned that the only age category which can furthermore register as unemployed, namely the 15–19 years old, experience a lower-than-average unemployment rate. This age category was included in earlier versions of our model and its coefficient was actually negative, although not significantly. Nevertheless, compared to the 15–19 years old, the 20–24 and 15-64 years old people experience higher unemployment rates, and thus unemployment should rise with their population share. When comparing the coefficients of the included age categories, we see that the coefficient of the 20–24 years old is higher than the one for the 25–64 years old. This reflects the fact that the 20–24 years old people experience a clearly higher-than-average unemployment rate.

Sectoral Employment

The effects of the sectoral employment mix on unemployment are not a priori clear, as different argumentations are possible. This is reflected in the mixed results of including the sectoral employment shares (Elhorst, 1995, Partridge and Rickman, 1995, 1997, Taylor and Bradley, 1997). Armstrong and Taylor (1993) argue that the unemployment rate is not specific to regions, but to industries. Therefore, they explain the unemployment rate in a specific region by its industry mix and the national rate of unemployment in each industry. But as Martin (1997) shows, the unemployment rate of a specific industry can be different in different regions.

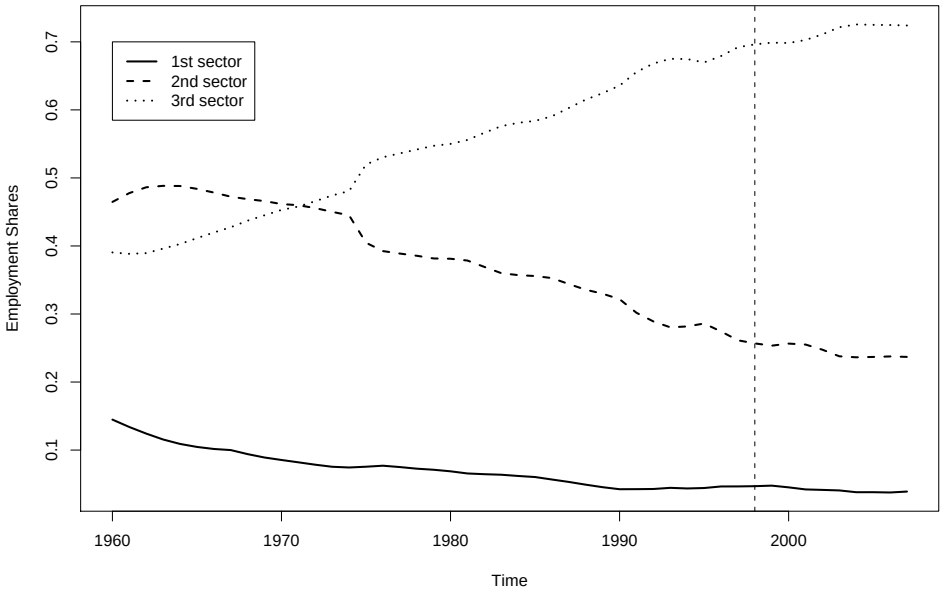
An important phenomenon in the context of sectoral employment and unemployment is the tertiarization process, which is supposed to cause unemployment to be higher in regions specialized in agriculture and manufacturing than in regions specialized in services. As Sheldon (1999) points out, Switzerland was confronted with a tertiarization of the working environment since the 1960s. Employment in production and manufacturing decreased, while the services sector showed an increase in employment and added value. Steffen (2005) thus supposes that cantons with a large manufacturing sector have a larger number of endangered jobs. In cantons with a large service sector, tertiarization is more advanced and the number of endangered jobs is smaller. However, the estimations conducted by Steffen (2005) indicate that unemployment rises with the employment share of the services sector. As it seems, tertiarization is not the only channel through which the sectoral mix affects unemployment.

An argument in the opposite direction can be made using employment multipliers. The former are generally higher in agriculture and manufacturing than in the services sector, given that the first two sectors – at least partly – create the demand for some services (Elhorst, 2003). Consequently, unemployment could fall with the employment shares of the first two sectors. With regard to the first sector, the following argumentation can additionally be made: enterprises in the agriculture sector are frequently family enterprises. If a family member loses his/her job outside the farm, he/she often can work on the farm and does not register as unemployed. Furthermore, social control is rather strong in regions with a high employment share of the first sector, i.e. people who lost their job may register less frequently as unemployed than in other regions because they feel ashamed. A high employment share of the first sector could thus dampen unemployment not through economic, but through psychological mechanisms.

In our study, we would not expect tertiarization to play a dominant role as we use data from 1998 to 2007. Figure 5 shows that the process of tertiarization was quite advanced in 1998. Although the employment shares changed further during our sample, the main part of the evolution was already completed. With respect to the second sector, we can furthermore say that those industries that still produced in Switzerland in 1998 were mainly high tech industries. They may have a rather high employment multiplier and be less affected by tertiarization.

Similar to Oud et al. (2008), we measure the economic structure as the proportion of employment in agriculture, manufacturing and services. In our estimations, we include the shares in employment of the second and the third sector in the explanatory variables.

Figure 5: *Employment Shares of the Sectors.*



NOTE: The dotted line shows 1998, the begin of our sample.

While the coefficient of the second sector is not significant (and thus not reported), the coefficient of the third sector is positive. A higher employment share of the third sector therefore increases unemployment. We thus conclude that tertiarization does indeed not dominate our result. Instead, higher employment multipliers, robust industries, familial job opportunities and social control seem to decrease unemployment in the first and the sector sector.

Besides the breakdown into the three sectors, we also analyze the internal structure of the modernity of the industries and discriminate three stages: traditional, modern and high-tech industries. The share of employment in traditional industries is supposed to increase unemployment as the former are generally declining. On the other hand, the employment share of high-tech industries should decrease unemployment as these are only little affected by structural change. The same argument can be mode for modern industries. Surprisingly, we only find a significant effect for the modern industries: the higher the share of employment in modern industries, the higher is unemployment. We explain this result with the bursting of the "dot-com-bubble", which falls into our estimation sample and caused unemployment among bankers and IT engineers to increase considerably. As modern industries mainly include the financial sector and IT, this one-time shock could explain our result.

Industrial Concentration

Industrial diversity – the opposite of industrial concentration – is the dispersion of employment over industries. Several studies suggest that it is negatively related to unemployment. The idea is that regions with multiple sources of employment provide more chances to become re-employed. Elhorst (2001) cites five studies investigating the relationship between unemployment and industrial diversity (Taylor and Bradley, 1983, Neumann and Topel, 1991, Malizia and Ke, 1993, Simon, 1988, Partridge and Rickman, 1995). All of them find the expected effect. However, it is significant in the first three studies only. On the other hand, one might also argue that concentration in employment is a sign for industrial clustering, which leads to network effects. These can lower unemployment.

The dispersion of employment over the industries is measured by the Herfindahl index. Originally developed to measure the amount of competition among firms, it has undergone several adaptions for other purposes. The idea is to calculate an index of the concentration of output over firms, employment over industries etc. It is calculated as $H = \sum_{i=1}^{N} s_i^2$ with N: number of industries, s_i: share of employment in industry i. It reaches a maximum of

1 in the case of total concentration of employment in one industry. Smaller values indicate more equally distributed employment.

For Switzerland, Filippini (1998) assumes economies with a larger dispersion of employment to show more stable GDP growth and lower unemployment rates than economies specialized in fewer industries. This is confirmed by the findings of Steffen (2005). In contrast, we find a concentration of employment in few industries to lower unemployment. The benefits of clustering seem to dominate the gains of diversification. The differences to the results of the above cited studies may be due by the varying samples used.

This effect only exists in the non-spatial setting. When including spatial elements, the effect of industrial concentration is not significant any more.

Public Sector

As stated by Steffen (2005), the share of employment of the public sector is assumed to have a dampening effect on unemployment. The argument for this is twofold: Firstly, the public sector is less affected by economic crises (see Forni, 2002), and secondly, the enlargement of public employment in times of economic crises can dampen the raise in unemployment (Armingeon, 1999). Other studies (see, e.g., Parnisari, 2003) put it another way and state that a large share of employment in industries with a low responsiveness to the business cycle lower the variance of unemployment.

Steffen (2005) includes the share of employment of the public sector in her models. She cannot find a significant effect in any of the estimated models. In contrast to Steffen (2005), but in line with the above mentioned theory, we find a slight, but negative effect.

Population Density

Population density is often taken as a proxy for the market potential of a region. It is sometimes called potential demand or agglomeration potential. The idea is that through the mechanisms of economies of scale and transport costs, firms tend to produce – and thus demand labor – in regions with high population density. Elhorst (1995) and Molho (1995a,b) model the regional unemployment rate as dependent on the market potential. They all find a negative and significant effect of the market potential on the regional unemployment rate. On the other hand, there is also an intuitive argument for the opposite direction: unemployed people may rather move into the cities as they can benefit from the nearby services and vacancies.

In Switzerland, population density is very different across cantons. In the two urban cantons Basel-Stadt and Geneva it is very high while in more rural cantons as the Grisons or Uri it is quite low. The maximum is reached by Basel-Stadt with more than 5000 people per km^2, in Geneva it is about 1500 people per km^2. As we have discussed above, these two border cantons are confronted with a large number of cross-border commuters. The nation-wide mean population density is 187 people per km^2 and the minimum lies at 25 persons per km^2 in the Grisons. In general, population density is negatively correlated with the share of persons occupied in the first sector (cf. Figure 6).

In our estimations, we find a significant positive effect of the population density on unemployment. This contradicts the presented theory, but is in line with the intuition.

As mentioned, there is a high correlation with cross-border commuters in the cantons Basel-Stadt and Geneva. As these two cantons could influence the estimates for population density much, we checked the robustness by estimating our model without these two cantons. The result is given in Table 4. We see that the coefficient for population density becomes insignificant when Basel Stadt and Geneva are excluded from the sample while all other coefficients are stable. This result is more in line with the theory than the result when considering all cantons.

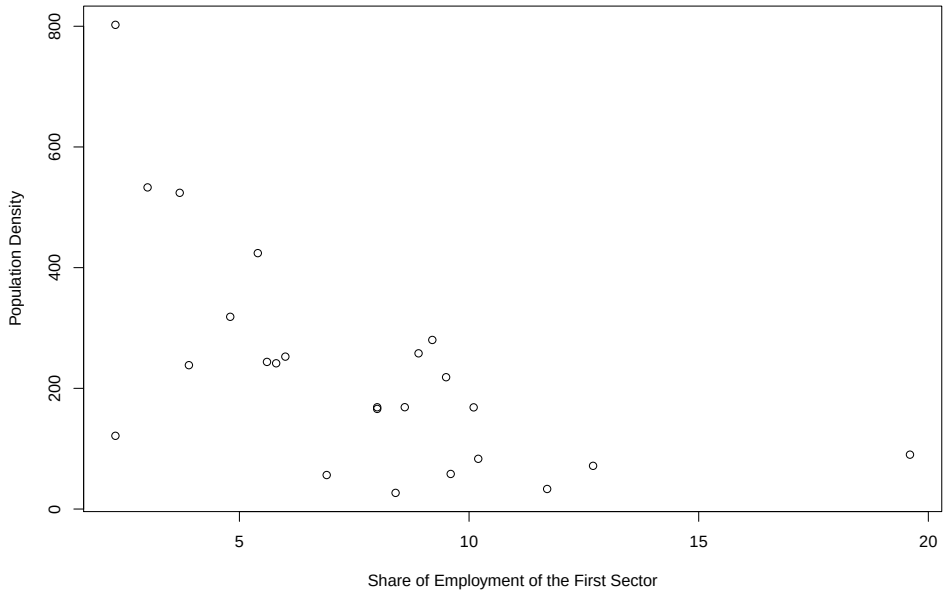
GDP

One of the most widely used variables for labor demand is the regional GDP in real terms. The relation is assumed to be positive, i.e. we expect a negative relation to unemployment.

Feld and Savioz (2000) use cantonal GDP for explaining cantonal unemployment rates. In their estimations, they find a negative – but insignificant – effect. Only when aggregating the 26 cantons to seven NUTS-2 regions, the effect becomes significant. Steffen (2005) finds a negative – and for some models even significant – effect of GDP growth on regional unemployment. She reasons that cantonal economic growth is important for describing the different levels of unemployment, but it is not their main determinant.

As in Switzerland there is no quarterly data for the regional GDP, we use the national GDP instead. We include annualized quarter-on-quarter GDP growth with a lead of one quarter and individual coefficients to our model. The coefficients can then be interpreted as elasticities. Figure 7 illustrates the cantonal elasticities of the unemployment rate to GDP. The strongest reactions are registered in Geneva, Zurich, Jura and Neuchâtel. On the other hand, only small elasticities are registered in Appenzell Inner Rhodes and Outer Rhodes, Ticino, Obwalden and Nidwalden.

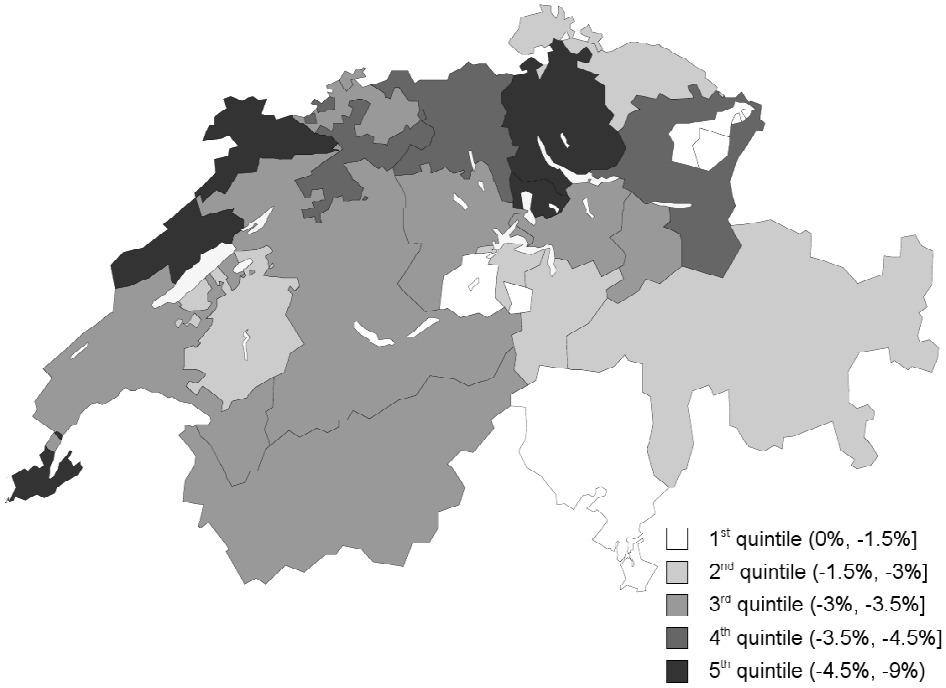
Figure 6: *Employment Share of the First Sector and Population Density.*



NOTE: The values for Basel Stand and Geneva are outside the panel. They both have a small share of employment in the first sector and a very large population density.

As the coefficients for the elasticity to GDP are quite similar across the cantons, we test them on equality. The corresponding F-Test rejects the equality of equal elasticities. We therefore need individual coefficients for GDP.

Figure 7: *Elasticities of Swiss Cantons to a Change in National GDP.*



NOTE: The strongest reactions are registered in Geneva, Zurich, Jura and Neuchâtel. On the other hand, only small elasticities are registered in Appenzell Inner Rhodes and Outer Rhodes, Ticino, Obwalden and Nidwalden.

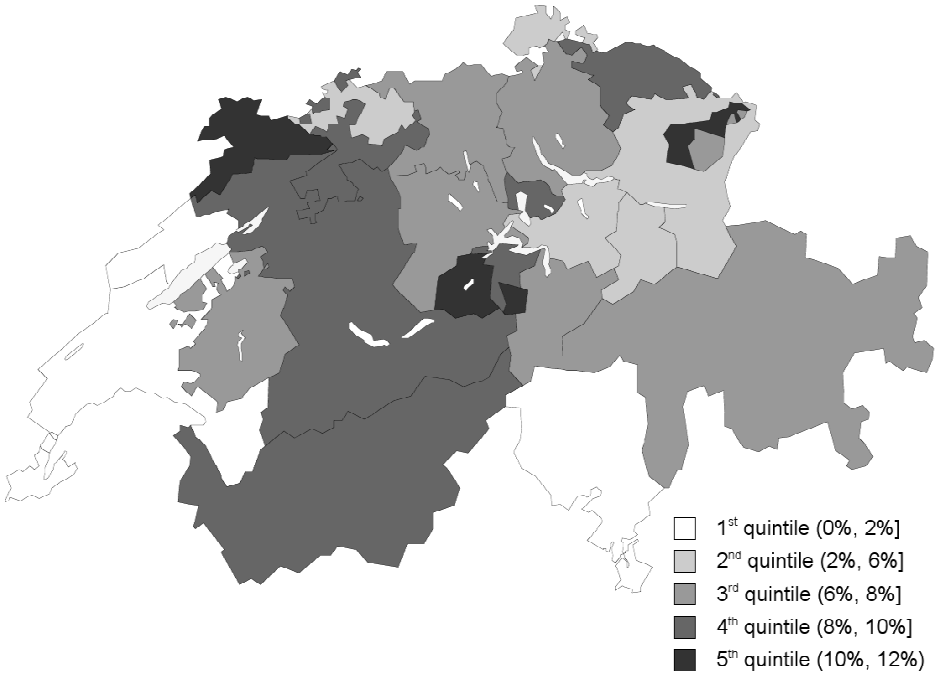
Wages

The wage level represents the price of labor and has been used in many studies (Steffen, 2005, Filippini, 1998, Burridge and Gordon, 1981, Hofler and Murphy, 1989, Partridge and Rickman, 1995, Molho, 1995b,a, Partridge and Rickman, 1997). Wages are usually believed to have a positive effect on labor supply and a negative effect on labor demand, hence unemployment should increase if wages rise. Indeed, most Swiss and international studies analyzing the effect of wages on unemployment find a positive relationship (cf., e.g., Steffen, 2005, Filippini, 1998, Burridge and Gordon, 1981, Hofler and Murphy, 1989, Partridge and Rickman, 1995, 1997).

As a measure for wages, we use the wage index of the Swiss Federal Statistical Office, which records the evolution of the national mean wage. This index excludes bonuses and measures the change in the fees paid for given tasks. In other words, it is a good index for the evolution of unit labor costs, rather than a general income measure. We include annualized quarter-on-quarter growth rates of the wage index in our model. As we have no regional data for the wage index, we allow the cantons to have individual elasticities. In line with the above mentioned literature, we find a positive effect of the wages on unemployment in all cantons. Figure 8 illustrates the cantonal elasticities of the unemployment rate to the wages. With the exception of Jura, the Latin speaking cantons show lower elasticities than the German ones.

Again, we conduct an F-Test to check whether we really need individual wage elasticities. The null hypothesis of one equal coefficient is clearly rejected.

Figure 8: *Elasticities of Swiss Cantons to a Change in National Wages.*



NOTE: With the exception of Jura, the Latin speaking cantons show lower elasticities than the German ones.

Constants

Studies analyzing the different levels in the unemployment rates across regions often use individual constants to summarize all unobserved cross-section specific factors. An F-test clearly indicates that these individual constants should not be summarized into one common intercept in our model.

5.2 Model Fit

To evaluate how well our model fits the data, we use two benchmark models (results on the coefficients are not reported): A model with the same exogenous explanatory variables but without spatial components ("OLS model") and a naive autoregressive model, containing individual constants and a common AR-coefficient for all cross-sections ("AR model"). In both models, the coefficient of the time lag of the dependent variable is considerably higher than in the spatial model (OLS model: 0.90; AR model: 0.92). This is due to the high persistence of the unemployment rates: a part of the information that was contained in the spatial lags is now captured by the time lag.

To compare the results of the spatial model to those of the benchmark models, we measure the in-sample fit of the three models. However, there are several possibilities of how to fit the endogenous variable: While for the OLS model and the AR model, the information to use for the fit clearly consists of the actual values of the exogenous variables and the temporally lagged dependent variable, for the spatial model, we may furthermore include the spatial lag (i.e., the contemporaneous values of the dependent variable). Kelejian and Prucha (2007) present four predictors for spatial models, based on different information sets:[6]

$$\begin{aligned} \Lambda_1 &= \{X_t, W\} \\ \Lambda_2 &= \{X_t, W, w_{i.} y_t\} \\ \Lambda_3 &= \{X_t, W, y_{-i,t}\}, \end{aligned} \tag{5.1}$$

where $w_{i.}$ denotes the i-th row of W and $y_{-1,t}$ denotes the y_t vector from which the i-th element has been removed. Information set Λ_1 is thus a subset of Λ_2 which again is a subset

[6] Kelejian and Prucha (2007) define their predictors for a cross-sectional model. We adapt their predictors for a time series model. A fifth predictor which is presented in their paper refers to the spatial error model without spatial lag in the dependent variable and is thus not adequate for our model.

of the full information set Λ_3. The first three predictors which Kelejian and Prucha (2007) present are the conditional means corresponding to the information sets Λ_p, $p = 1, 2, 3$, in (5.1):

$$\begin{aligned} y_{it}^{(1)} &= E(y_{it}|\Lambda_1) \\ &= (I - \rho_1 W)_{i.}^{-1} x_t \beta \end{aligned} \tag{5.2}$$

$$\begin{aligned} y_{it}^{(2)} &= E(y_{it}|\Lambda_2) \\ &= \rho_1 w_{i.} y_t + x_{ti.}\beta + \frac{cov(u_{it}, w_{i.}y_t)}{var(w_{i.}y_t)}[w_{i.}y_t - E(w_{i.}y_t)] \end{aligned} \tag{5.3}$$

$$\begin{aligned} y_{it}^{(3)} &= E(y_{it}|\Lambda_3) \\ &= \rho_1 w_{i.} y_t + x_{ti.}\beta + cov(u_{it}, y_{-i,t}) \left[VC(y_{-i,t})\right]^{-1} \left[y_{-i,t} - E(y_{-i,t})\right] \end{aligned} \tag{5.4}$$

where VC denotes the variance-covariance matrix. Calculational details are given in Kelejian and Prucha (2007). The fourth predictor they consider is given by

$$y_{it}^{(4)} = \rho_1 w_{i.} y_t + x_{i.t}\beta \tag{5.5}$$

This predictor may be seen as a restricted version of predictor $y_{it}^{(2)}$, implicitly assuming that $cov(u_{it}, w_{i.}y_t) = 0$. This does, however, not hold in general. Thus, conditional on the information set Λ_2, predictor 4 is biased. Kelejian and Prucha (2007) find that predictor 3, which uses the full information set Λ_3, empirically performs best.

To compare the predictors, we measure the goodness of fit by the root mean squared error (RMSE) and the adjusted R^2. Tables 1 and 2 show the ranks which the predictors of the spatial model and the benchmark models reach as measured by these criteria[7]. Furthermore, figures 9 and 10 show boxplots of the distribution of the model fit criteria through the cross-sections. We see that predictors 2 and 3 of the spatial model together reach by far the best ranks. Measured by the RMSE ranks, predictor 2 even seems to outperform predictor 3. However, the corresponding boxplots show that the RMSEs of the two predictors are distributed similarly. The adjusted R^2 indicates that the two predictors perform roughly the same as well. This result indicates that in our context, there is no

[7]For the RMSE themselves, see Table 5

Table 1: *Root Mean Squared Error of the Different Predictors, Ranks.*

	Sp. Pred. 1	Sp. Pred. 2	Sp. Pred. 3	Sp. Pred. 4	OLS	AR
1st	0	15	9	2	0	0
2nd	1	8	16	1	0	0
3rd	0	2	0	17	7	0
4th	9	0	1	6	10	0
5th	16	0	0	0	9	1
6th	0	1	0	0	0	25

Table 2: *Adjusted R squared of the Different Predictors, Ranks.*

	Sp. Pred. 1	Sp. Pred. 2	Sp. Pred. 3	Sp. Pred. 4	OLS 2	AR
1st	0	12	11	2	1	0
2nd	1	12	13	0	0	0
3rd	0	1	1	14	8	2
4th	10	0	1	9	5	1
5th	13	0	0	1	12	0
6th	2	1	0	0	0	23

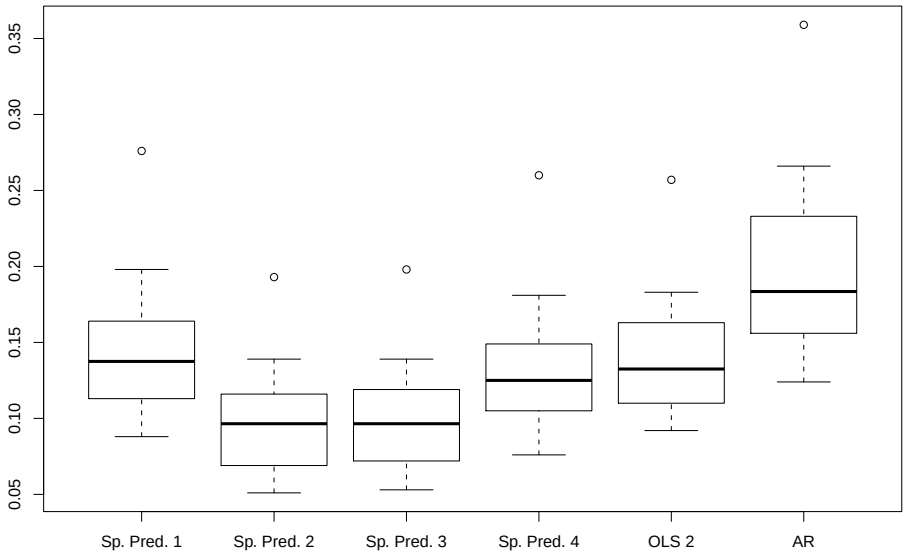
NOTE: Predictors 2 and 3 of the spatial model together reach by far the best ranks. Predictor 2 even obtains the best fit more often than Predictor 3. Predictors 4 and 1 and the OLS model follow, while the AR model performs clearly the worst.

clear difference between the information sets Λ_2 and Λ_3, or rather between the information contained in $w_{i.}y_t$ and $y_{-i,t}$. In words, knowing the weighted mean of the unemployment rates in all other cantons is roughly the same as knowing the actual unemployment rates in the other cantons. This implies that our W matrix is a good measure for the interdependencies between the cantonal labour markets. Behind predictors 2 and 3, predictors 4 and 1 and the OLS model follow. The AR model, which uses the smallest information set of all predictors, clearly performs the worst.

5.3 Emanating effects

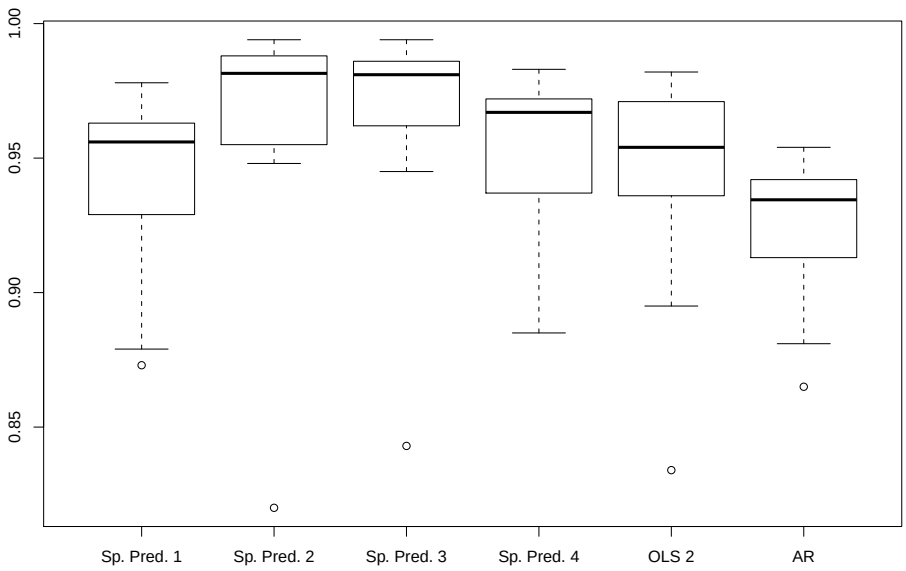
We now use our model to calculate the emanating effects of a change in the explanatory variables. We run an alternative scenario assuming a reduction of cross-border commuters by 10% from the first quarter 2003 onwards in all cantons as compared to the actual values.

Figure 9: *Root Mean Squared Error of the Different Predictors.*



NOTE: Predictor 2 reaches the best performance for some cross-sections, but performs worse than predictor 3 for some others.

Figure 10: *Adjusted R squared of the Different Predictors.*



NOTE: Predictor 2 reaches the best performance for some cross-sections, but performs clearly worse than predictor 3 for some others. Not surprisingly, the models using less information perform worse.

We then compare the resulting unemployment rates with the fitted unemployment rates in our model which result using the actual values. A change as assumed in our scenario might be caused by a more restrictive handling of border commuting. Such policies are sometimes called for as a measure against unemployment in border cantons. A reduction of cross-border commuters would not only influence unemployment directly in all cantons which record cross-border commuters, but by spatial effects also indirectly in all other cantons. As the coefficient of the share of cross-border commuters is negative in our model, reducing the number of cross-border commuters will ceteris paribus lower unemployment.

The emanating effects of a change in one or more explanatory variables can be calculated by rewriting the model (4.4) as follows (see, e.g., Kelejian et al., 2008):

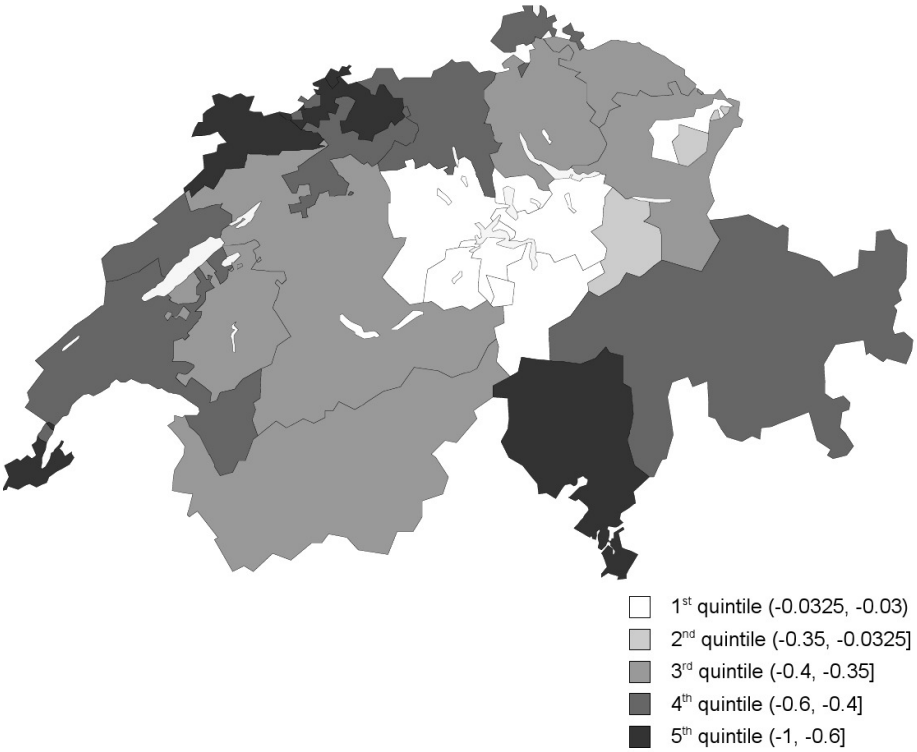
$$y_t = (I - \rho_1 W)^{-1} X_t \beta + (I - \rho_1 W)^{-1} u_t \tag{5.6}$$

Let $(I-\rho_1 W)^{-1} X_t \beta$ be the $N \times 1$ vector of values resulting from the actual values of X_t. Furthermore, let $(I - \rho_1 W)^{-1} X_t \beta|_{alt}$ denote the corresponding values for our alternative scenario. Assuming that the error terms remain unchanged, the emanating effects can then be calculated as the difference between these values:

$$(I - \rho_1 W)^{-1} X_t \beta|_{alt} - (I - \rho_1 W)^{-1} X_t \beta \tag{5.7}$$

Table 3 shows the detailed emanating effects, i.e. the differences which result from the reduction in cross-border commuting. The effects are listed for the yearly average unemployment rate. The emanating effects grow over time, but the increases diminish towards the end of the horizon. This increase over time is due to the auto-regressive structure of our model, where the differences in one period have an impact on the differences in the following periods. The new equilibrum lies up to 1.16 percentage point below the initial values for Basel-Stadt, whereas almost no effect at all is visible in Uri, Schwyz and Zug. Figure 11 shows the geographical dispersion of the emanating effects four years after the change in commuting. Not surprisingly, the strongest results are registered in the border cantons in general, and especially in Basel-Stadt, Basel-Land, Jura, Geneva and Ticino. These five cantons record the highest share of cross-border commuters and thus experience the highest reduction of commuters in our alternative scenario. The more centrally situated cantons on the other hand experience small effects only. Some central cantons record no

Figure 11: *Emanating Effects in the Year 2007 for the Alternative Scenario of a Reduction in Cross-Border Commuters.*



NOTE: Annual average in official unemployment rates.

cross-border commuters at all (and therefore no reduction in the alternative scenario) and only experience indirect effects.

A word of caution about the results discussed here is in order. We have run an alternative scenario assuming that all explanatory variables except the number of cross-border commuters remain unchanged. We would, however, expect a forced reduction in the number of cross-border commuters to have an impact on some of the other explanatory variables. Especially GDP could be affected negatively, which in turn would raise unemployment. In order to determine the dynamic effects of our scenario, we would need to determine the affected explanatory variables endogenously in the model. Therefore, our static analysis cannot determine whether a reduction in the number of cross-border commuters would raise or lower unemployment once all direct and indirect effects are taken into account. It should merely be seen as an illustration of the dispersion of the immediate effects. Because

Table 3: *Emanating Effects for the Alternative Scenario of a Reduction in Cross-Border Commuters.*

	2003	2004	2005	2006	2007
AG	−0.05	−0.14	−0.24	−0.34	−0.44
AI	−0.02	−0.08	−0.16	−0.24	−0.34
AR	−0.02	−0.08	−0.15	−0.23	−0.32
BE	−0.02	−0.09	−0.17	−0.27	−0.37
BL	−0.15	−0.35	−0.51	−0.65	−0.78
BS	−0.32	−0.66	−0.86	−1.02	−1.16
FR	−0.02	−0.08	−0.17	−0.26	−0.36
GE	−0.17	−0.38	−0.54	−0.69	−0.83
GL	−0.02	−0.08	−0.15	−0.24	−0.33
GR	−0.05	−0.14	−0.22	−0.32	−0.41
JU	−0.13	−0.29	−0.43	−0.56	−0.7
LU	−0.02	−0.07	−0.14	−0.23	−0.32
NE	−0.07	−0.19	−0.3	−0.41	−0.54
NW	−0.02	−0.07	−0.14	−0.22	−0.32
OW	−0.02	−0.07	−0.14	−0.22	−0.32
SG	−0.04	−0.11	−0.18	−0.26	−0.36
SH	−0.11	−0.24	−0.35	−0.46	−0.58
SO	−0.03	−0.11	−0.2	−0.3	−0.4
SZ	−0.02	−0.07	−0.14	−0.22	−0.31
TG	−0.04	−0.12	−0.21	−0.3	−0.4
TI	−0.21	−0.44	−0.59	−0.72	−0.85
UR	−0.02	−0.07	−0.14	−0.22	−0.31
VD	−0.06	−0.15	−0.26	−0.36	−0.47
VS	−0.03	−0.11	−0.2	−0.3	−0.4
ZG	−0.02	−0.07	−0.14	−0.22	−0.31
ZH	−0.02	−0.09	−0.17	−0.26	−0.36

NOTE: Annual averages in official unemployment rates.

of the spatial lag in the model, the cantons that do not record cross-border commuters at all are hit indirectly via the changed unemployment rate of other cantons.

6 Conclusions

In this paper, we estimate a spatial time series model for the Swiss cantonal unemployment rates. This allows us to determine the variables which explain the levels and fluctuations in the regional unemployment rates and investigate whether these variables retain their explanatory power once spatial elements are added to the model. As we find spatial dependency in the levels as well as in the errors, we estimate a SARAR(1,1) model. Our estimation results indicate that spatial spillovers have additional explanatory power to our other model variables.

Furthermore, we find that regional unemployment is raised by the population shares of women, of cross-border commuters and of people aged between 20 and 24 as well as between 25 and 64, by the population density, by the employment share of the third sector and of modern industries and by wage growth. On the other hand, we find decreasing effects by the employment share of the public sector and by GDP growth. Most of these findings are consistent with the existing literature on regional unemployment levels. We then compare the predictions of the spatial model to some alternative models. We see that our spatial model reaches a better fit than a benchmark model which uses the same explanatory variables but no spatial lags.

The possibilities of hypothesis testing with our model are restricted by the availability of quarterly regional data. Furthermore, the data we have at hand is often disposable for short time periods only. As data availability improves over time, expansions of our model might well be possible in the future.

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A Appendix

A.1 Generalized moments procedure

This section outlines the generalized moments procedure proposed by Kelejian and Prucha (1998), which produces an estimator for the parameter ρ_2. The point of departure are the following transformations of equation (4.7):

$$u - \rho_2 W_{NT} u = \epsilon \tag{A.1}$$

$$W_{NT} u - \rho_2 W_{NT}^2 u = W_{NT} \epsilon \tag{A.2}$$

We define u_i, $\overline{u}_i$ and $\overline{\overline{u}}_i$ to be, respectively, the i-th elements of u, $\overline{u} = W_{NT} u$ and $\overline{\overline{u}} = W_{NT}^2 u$. Similarly, we define ϵ_i and $\overline{\epsilon}_i$ to be the i-th elements of ϵ and $\overline{\epsilon} = W_{NT}\epsilon$. We can then write the above equations as follows:

$$u_i - \rho_2 \overline{u}_i = \epsilon_i, \qquad i = 1, ..., NT \tag{A.3}$$

$$\overline{u}_i - \rho_2 \overline{\overline{u}}_i = \overline{\epsilon}_i, \qquad i = 1, ..., NT \tag{A.4}$$

By squaring and then summing both equations, multiplying (A.3) by (A.4) and summing and finally dividing all terms by NT, the following system of equations is constructed:

$$2\rho_2 \frac{1}{NT} \sum u_i \overline{u}_i - \rho_2^2 \frac{1}{NT} \sum \overline{u}_i^2 + \frac{1}{NT} \sum \epsilon_i^2 = \frac{1}{NT} \sum u_i^2 \tag{A.5}$$

$$2\rho_2 \frac{1}{NT} \sum \overline{u}_i \overline{\overline{u}}_i - \rho_2^2 \frac{1}{NT} \sum \overline{\overline{u}}_i^2 + \frac{1}{NT} \sum \overline{\epsilon}_i^2 = \frac{1}{NT} \sum \overline{u}_i^2 \tag{A.6}$$

$$\rho_2 \frac{1}{NT} \sum (u_i \overline{\overline{u}}_i + \overline{u}_i^2) - \rho_2^2 \frac{1}{NT} \sum \overline{u}_i \overline{\overline{u}}_i + \frac{1}{NT} \sum \epsilon_i \overline{\epsilon}_i = \frac{1}{NT} \sum u_i \overline{u}_i \tag{A.7}$$

As a next step, expectations are taken across the system and the terms involving ϵ replaced as follows:

$$E\left(\frac{1}{NT} \sum \epsilon_i^2\right) = \sigma_\epsilon^2 \tag{A.8}$$

$$E\left(\frac{1}{NT} \sum \overline{\epsilon}_i^2\right) = \frac{1}{NT} \sigma_\epsilon^2 tr(W_{NT}' W_{NT}) \tag{A.9}$$

$$E\left(\frac{1}{NT} \sum \epsilon_i \overline{\epsilon}_i\right) = 0, \tag{A.10}$$

where $tr(.)$ denotes the trace operator. While (A.8) and (A.9) follow from assumption (4.3), (A.10) additionally makes use of the fact that all diagonal elements of W_{NT} are zero. The system of equations can now be written as follows:

$$\Gamma(\rho_2, \rho_2^2, \sigma_\epsilon^2)' - \gamma = 0 \tag{A.11}$$

where

$$\Gamma = \frac{1}{NT}\begin{pmatrix} 2E(u'\overline{u}) & -E(\overline{u}'\overline{u}) & NT \\ 2E(\overline{\overline{u}}'\overline{u}) & -E(\overline{\overline{u}}'\overline{\overline{u}}) & tr(W_{NT}'W_{NT}) \\ 2E(u'\overline{\overline{u}} + \overline{u}'\overline{u}) & -E(\overline{u}'\overline{\overline{u}}) & 0 \end{pmatrix} \tag{A.12}$$

$$\gamma = \frac{1}{NT}\begin{pmatrix} E(u'u) \\ E(\overline{u}'\overline{u}) \\ E(u'\overline{u}) \end{pmatrix} \tag{A.13}$$

The expectations are next replaced by their sample analogues using $\tilde{u}$ from the two-stage least squares regression in the first estimation step. Equation (A.11) can then be solved by nonlinear least squares to get the estimators $\hat{\rho}_2$ and $\hat{\sigma}_\epsilon^2$.

A.2 Estimated Coefficients

Table 4: *Estimation Results.*

	Selected Model	Full Model	Robustness Check	Non-Spatial Model
Temporal Lag	0.81***	0.81***	0.82***	0.90***
	(0.02)	(0.02)	(0.02)	(0.01)
Spatial Lag (ρ_1)	0.18***	0.18***	0.17***	
	(0.02)	(0.05)	(0.02)	
Spatial Error Lag (ρ_2)	0.64***	0.63***	0.64***	
	(0.05)	(0.02)	(0.00)	
Cross border commuters	0.09***	0.09***	0.10***	0.12***
(% share in total population)	(0.01)	(0.01)	(0.02)	(0.01)
Women	0.21***	0.21***	0.21***	0.40***
(% share in total population)	(0.04)	(0.04)	(0.04)	(0.05)
Population Density	0.97***	0.96***	1.43	0.68*
(population in 1000 per km^2)	(0.30)	(0.30)	(1.20)	(0.38)
Population aged 20-24	0.06**	0.06**	0.06**	0.21***
(% share in total population)	(0.03)	(0.03)	(0.03)	(0.03)
Population aged 25-64	0.04***	0.04***	0.05***	0.11***
(% share in total population)	(0.02)	(0.02)	(0.02)	(0.02)
Size of Public Sector	−0.02**	−0.02**	−0.02**	−0.05***
(% share in FTE employment)	(0.01)	(0.01)	(0.01)	(0.01)
Industrial Concentration		−3.94		−14.56*
		(4.15)		(6.12)
Size of 3rd Sector	0.01***	0.01***	0.02***	0.04***
(% share in FTE employment)	(0.01)	(0.01)	(0.01)	(0.01)
Size of Modern Industries	0.02**	0.02***	0.01*	0.08***
(% share in FTE employment)	(0.01)	(0.01)	(0.01)	(0.01)
Observations	1040	1040	1040	1040

NOTE: Omitted variables are constants as well as GDP and wage elasticities. Standard errors in parentheses; * significant at the 90% confidence level; ** significant at the 95% confidence level; *** significant at the 99% confidence level; FTE: full-time equivalent

A.3 Root Mean Sqared Error of the Different Predictors

Table 5: *Root Mean Sqared Error of the Different Predictors.*

	Sp. Pred. 1	Sp. Pred. 2	Sp. Pred. 3	Sp. Pred. 4	OLS	AR
AG	0.14	0.06	0.06	0.12	0.12	0.19
AI	0.15	0.10	0.10	0.14	0.14	0.15
AR	0.16	0.11	0.11	0.14	0.12	0.16
BE	0.12	0.05	0.06	0.11	0.10	0.18
BL	0.11	0.07	0.07	0.09	0.10	0.18
BS	0.15	0.09	0.09	0.13	0.15	0.22
FR	0.09	0.09	0.08	0.08	0.10	0.16
GE	0.17	0.12	0.12	0.16	0.15	0.26
GL	0.15	0.09	0.10	0.13	0.14	0.18
GR	0.11	0.09	0.08	0.09	0.10	0.14
JU	0.28	0.19	0.20	0.26	0.26	0.36
LU	0.14	0.07	0.08	0.13	0.14	0.19
NE	0.16	0.12	0.12	0.15	0.18	0.25
NW	0.10	0.07	0.07	0.09	0.13	0.14
OW	0.12	0.11	0.11	0.11	0.13	0.14
SG	0.11	0.06	0.07	0.09	0.09	0.16
SH	0.17	0.12	0.12	0.15	0.18	0.22
SO	0.20	0.12	0.12	0.18	0.18	0.27
SZ	0.11	0.07	0.07	0.10	0.13	0.16
TG	0.12	0.05	0.05	0.11	0.11	0.18
TI	0.14	0.13	0.12	0.13	0.17	0.23
UR	0.11	0.13	0.12	0.11	0.12	0.12
VD	0.13	0.10	0.09	0.12	0.14	0.22
VS	0.17	0.14	0.14	0.16	0.18	0.24
ZG	0.14	0.10	0.10	0.12	0.11	0.21
ZH	0.17	0.11	0.11	0.16	0.16	0.25
Median	0.14	0.10	0.10	0.13	0.13	0.18