University of Groningen

A regional unemployment model simultaneously accounting for serial dynamics, spatial dependence and common factors

Halleck Vega, Solmaria; Elhorst, J. Paul

Published in:
Regional Science and Urban Economics

DOI:
[10.1016/j.regsciurbeco.2016.07.002](https://doi.org/10.1016/j.regsciurbeco.2016.07.002)

IMPORTANT NOTE: You are advised to consult the publisher's version (publisher's PDF) if you wish to cite from it. Please check the document version below.

Document Version
Publisher's PDF, also known as Version of record

Publication date:
2016

[Link to publication in University of Groningen/UMCG research database](#)

Citation for published version (APA):

Halleck Vega, S., & Elhorst, J. P. (2016). A regional unemployment model simultaneously accounting for serial dynamics, spatial dependence and common factors. *Regional Science and Urban Economics*, 60, 85-95. <https://doi.org/10.1016/j.regsciurbeco.2016.07.002>

Copyright

Other than for strictly personal use, it is not permitted to download or to forward/distribute the text or part of it without the consent of the author(s) and/or copyright holder(s), unless the work is under an open content license (like Creative Commons).

The publication may also be distributed here under the terms of Article 25fa of the Dutch Copyright Act, indicated by the "Taverne" license. More information can be found on the University of Groningen website: <https://www.rug.nl/library/open-access/self-archiving-pure/taverne-amendment>.

Take-down policy

If you believe that this document breaches copyright please contact us providing details, and we will remove access to the work immediately and investigate your claim.

Downloaded from the University of Groningen/UMCG research database (Pure): <http://www.rug.nl/research/portal>. For technical reasons the number of authors shown on this cover page is limited to 10 maximum.

A regional unemployment model simultaneously accounting for serial dynamics, spatial dependence and common factors[☆]

Solmaria Halleck Vega^{a,b}, J. Paul Elhorst^{a,*}

^a Faculty of Economics and Business, University of Groningen, PO Box 800, 9700 AV Groningen, The Netherlands

^b Paris School of Economics, Centre d'Economie de la Sorbonne, Université Paris 1 Panthéon-Sorbonne, 106/112 Blvd. de l'Hôpital, 75647 Paris Cedex 13, France

ARTICLE INFO

Article history:

Received 23 February 2016

Received in revised form 20 June 2016

Accepted 4 July 2016

Available online 6 July 2016

JEL classification:

C23

C33

C38

R23

Keywords:

Regional unemployment

Cross-sectional dependence

Dynamic spatial panel models

The Netherlands

ABSTRACT

Regional unemployment rates tend to be strongly correlated over time, parallel the national unemployment rate, and be correlated across space. We address these key stylized facts by linking different strands of literature into a unified methodology to investigate regional unemployment disparities. This methodology simultaneously accounts for serial dynamics, spatial dependence and common factors, also known as weak and strong cross-sectional dependence. We apply this approach using provincial level data for the Netherlands. The substantial and persistent division between high and low unemployment clusters makes it an interesting case, and data availability since the early 1970s enables a comparison between prior periods of downturn and recovery to the recent economic crisis. It is found that approaches that do not simultaneously account for serial dynamics, spatial dependence and common factors, or that ignore one of these issues, may lead to biased inference.

© 2016 Elsevier B.V. All rights reserved.

1. Introduction

The existence of substantial and persistent regional unemployment disparities is an economic, social, and policy concern.¹ Three noteworthy stylized facts that often emerge from observing the evolution of regional unemployment rates are that they tend to: (i) be strongly correlated over time, (ii) parallel the national unemployment rate, and (iii) be correlated across space. The first key point has been addressed in studies focusing on serial dynamic effects (e.g. Blanchard and Katz, 1992; Hyclak, 1996). The second key point pertains to literature on cyclical sensitivity (Thirlwall, 1966; Brechling, 1967)² and common factors (Pesaran,

2006). Regional unemployment rates tend to move in tandem with the national unemployment rate, but within the common rises and falls over time, the extent to which a region's rate responds to changes in the national rate can be quite heterogeneous. The third key point concerns spatial autocorrelation in unemployment rates due to interconnections between regions, which has received considerable attention in the regional science literature (e.g. Burridge and Gordon, 1981; Molho, 1995; Overman and Puga, 2002; Patacchini and Zenou, 2007). The spatial econometrics literature has developed methods to model these interconnections (see e.g., Anselin, 1988; LeSage and Pace, 2009).

Recently, growing attention is being paid to the difficulty in distinguishing between common factors and spatial dependence, where the former is also viewed as 'strong' cross-sectional dependence and the latter as 'weak' cross-sectional dependence in the literature (Chudik et al., 2011). In the context of regional unemployment rates, the observed correlation across space can be a result of shared factors such as business cycle effects, where outcomes change together as these factors change. However, this correlation can also be a result of local interactions between regions generating spillover effects. It is thus important to have a methodology that is able to address both forms of cross-sectional dependence (Kuersteiner and Prucha, 2015; Bailey et al. 2016). A recently proposed two-stage method is to first model common factors (e.g. aggregate shocks) using cross-sectional averages of the observations (Pesaran, 2006), and second, to

[☆] The authors gratefully acknowledge the Co-Editor Zhenlin Yang, two anonymous reviewers, Natalia Bailey, Alain Pirotte, Jan Oosterhaven, Carlo Ciccarelli, as well as the participants of seminars in Groningen, Oldenburg, Aachen, and the 15th International Workshop on Spatial Econometrics and Statistics in Orléans for their comments on a previous version of this paper.

* Corresponding author at: Faculty of Economics and Business, University of Groningen, PO Box 800, 9700 AV Groningen, The Netherlands.

E-mail addresses: s.m.halleck.vega@rug.nl, solmaria.halleck@psemail.eu, solmaria.halleck@univ-paris1.fr (S. Halleck Vega), j.p.elhorst@rug.nl (J.P. Elhorst).

¹ In light of the recent economic crisis, for example, there is concern that marked differences in unemployment across European regions will rise (Eurostat, 2014).

² A critical overview of 13 studies on regional unemployment cyclical sensitivity models can be found in Elhorst (2003, Section 2.1).

model the de-factored observations using spatial econometric techniques (Bailey et al., 2016).³

From the above, it can be concluded that studies on cyclical sensitivity that appeared back in the 1960s have paid attention to what can be termed common factors, and that spatial econometric studies have paid attention to spatial dependence. In this paper, we address the aforementioned stylized facts by linking these different strands of literature into a unified methodology. We propose an approach that simultaneously accounts for both forms of cross-sectional dependence, as well as serial dynamics. This contrasts two-step procedures that have been proposed in the literature, where the observations are first taken in deviation from their national average (US) as in Blanchard and Katz (1992) or continental average (EU) as in Decressin and Fatás (1995), first spatially filtered as in Getis and Griffith (2002) and Badinger et al. (2004), or first de-factored as in Bailey et al. (2016). The merging of serial dynamics, spatial dependence and common factors has been done in a series of papers to explain house prices (Holly et al., 2010, 2011; Bailey et al., 2016), but only sequentially and not to investigate regional unemployment disparities. Throughout this paper we use the terminology spatial dependence and common factors rather than weak and strong cross-sectional dependence, since these latter descriptions erroneously suggest that these forms of cross-sectional dependence are not equally important. We demonstrate that the descriptions common factors and spatial dependence do more justice to both properties of the data.

We apply the methods using data on overall unemployment for the Netherlands of 12 regions over the period 1973–2013 ($N = 12$, $T = 41$), which is interesting due to persistent high and low unemployment clusters, and changes in the compositions of these clusters. Moreover, data availability since the early 1970s enables a comparison between prior periods of downturn and recovery to the recent economic crisis.⁴ It is found that focusing only on serial dynamics and spatial dependence or common factors, or when employing a two-step rather than a simultaneous approach can bias the inferences that are drawn.

The remainder of this paper is organized as follows. Section 2 presents observed trends in unemployment rates across provinces in the Netherlands since the 1970s, highlighting the key stylized facts. Then, the methodology is outlined in Section 3, followed by the empirical results in Section 4. The final section provides concluding thoughts.

2. Evolution and stylized facts

Table 1 reports the correlation coefficients of the regional unemployment rates for observations made on all twelve regions with their counterparts one year, five years, ten years up to 40 years apart. These correlation coefficients appear to be large and to diminish slowly over time. This feature has been accounted for in some studies by incorporating serial dynamic effects, as in the classic study of Blanchard and Katz (1992) on regional labor market evolutions in the United States.⁵ Including these effects can have an important bearing on the results, and it is accordingly addressed in the model specification.

From observing regional unemployment rates alongside the national rate in Fig. 1, it is apparent that the broad movements have been quite similar over the past four decades. Five major economic downturns that have periodically inflicted unemployment rates emerge from

Table 1
Correlations of regional unemployment rates over time.

Year	1973	1974	1976	1981	1991	2001	2013
1973	1.00						
1974	0.82	1.00					
1976	0.67	0.95	1.00				
1981	0.45	0.73	0.83	1.00			
1991	0.34	0.43	0.41	0.67	1.00		
2001	0.37	0.35	0.36	0.57	0.73	1.00	
2013	−0.21	0.16	0.34	0.55	0.62	0.30	1.00

these figures. The first is the 1970s energy crisis- in particular, the 1973 oil shock and 1979 energy crisis- in which petroleum prices peaked substantially and compared to previous recessions was marked by stagflation. Typically, major shocks have longstanding effects and in the wake of the 1970s crises came the early 1980s recession. Unemployment rose considerably at the end of the 1970s and peaked in 1983–84. In the course of a decade, the unemployment rate in the Netherlands increased by 8 percentage points, reaching 10.7% in 1983. In Groningen and other northern provinces, the unemployment rate picked up even more swiftly, reaching a high of nearly 14% in 1983.⁶ A map of the twelve provinces in Netherlands with their (Dutch) names is provided in Fig. 2.

The mid-1980s gradually saw a fall in unemployment, but not to prior levels. In fact, some regions even had rocky trajectories from the late 1980s to early 1990s. Another notable feature is the major impact of the 1970s and early 1980s crises on levels of unemployment, which only dropped to pre-shock levels until the late 1990s and early 2000s. Following the recession of the early 1990s, unemployment peaked in 1994–96, although not as much as in 1983–84, as seen in Fig. 1. The national rate and regional rates also varied more in the timing of the peaks during this recessionary period. For example, the national rate peaked at 8.5% in 1994 and gradually decreased in 1995 and 1996, whereas in Groningen it rose during this same period from 11.1 to 12.1%.

Although there is debate that the 2000–01 recession was not as significant as the two previous widespread recessions, a quite substantial increase in unemployment occurred in the Netherlands a couple of years later with a peak in 2005 and subsequent dip in 2008. Due to the recent financial crisis of 2008, unemployment rapidly started picking up again and although the full impacts are still being felt, it can be seen that all regions have experienced increasing rates since 2008. The national rate has risen by 4.6 percentage points and the most striking increase has been experienced by Flevoland with a nearly 7 percentage point difference from the onset of the crisis.

Within the broad similarities in temporal patterns, it is also evident from Fig. 1 that there are variations across regions. The idea to link the regional to the national unemployment rate and to estimate this relationship for each single region dates back to Thirlwall (1966) and Brechling (1967), and is known as the regional cyclical sensitivity literature. Although this literature lost interest, the prevalence of recessionary shocks, and notably the recent crisis, makes it ever more pertinent to study regional cyclical sensitivity. Moreover, since the common factor literature based on cross-sectional averages developed by Pesaran (2006) and many related authors share the same central idea as explicitly demonstrated in the next section, this literature might become important again. By linking them in this paper, we hope to achieve that the cyclical sensitivity literature comes back into the picture again. Of particular importance is that regional heterogeneity is considered in both strands of literature.

Another striking observation from Fig. 1 is the quite constant persistence of above-average unemployment in Northern provinces, particularly Groningen. Flevoland has also generally exhibited higher

³ In their application of spatial econometric techniques, the latter study also considers using a correlation-based specification of the matrix of connections, a point we come back to in the results section.

⁴ Earlier economic downturns such as the 1973 oil shock and the early 1980s recession are difficult to analyze in a cross-country multiregional context because there is unfortunately no harmonized regional unemployment data across EU member states prior to 1983.

⁵ An overview of other studies including the serially lagged regional unemployment rate as an explanatory variable are provided in the introduction or can be consulted in Elhorst (2003). Another approach is to allow for the error term to be influenced by first-order autocorrelation, as in Partridge and Rickman (1997). A recent study combining serial and spatial dynamic effects is Patacchini and Zenou (2007).

⁶ Other countries were also hard-hit such as the United Kingdom where unemployment hit record numbers in the summer of 1984 (see for example, Martin, 1997).

Fig. 1. Regional compared to national unemployment rate, 1973–2013.

unemployment rates compared to the national rate over the period. In fact, it currently tops all regions, surpassing Groningen which has historically had the greatest unemployment problem. The other provinces have either been below or on a par with the national unemployment rate.

Fig. 2. The provincial map of the Netherlands.

Interestingly, these 'regional groupings' also form geographical clusters, which leads to the final key stylized fact.

Fig. 3 illustrates the geographical distribution of unemployment. Comparing 1973 to 1984, two main changes come into view. First, both the unemployment rates and the interregional differences were much smaller in 1973 than in 1984. The 1970s and early 1980s crises really made an enduring mark, especially on the Northern Netherlands. Over a decade later in 1996, the regional differences persist; Groningen, Friesland, and Drenthe still had greater unemployment than the rest of the country. In 2013, it can be seen that instead of Drenthe, Flevoland now joins neighboring region Friesland, as well as Groningen. The peripheral regions of Limburg and Zeeland are exceptions, with higher and lower unemployment compared to their respective neighboring Dutch provinces. Lower unemployment clusters surround Utrecht, even including the southern province North-Brabant for later periods shown.

It should be stressed that the patterns described in this section are not only typical for the Netherlands. Similar patterns have been identified in other studies, notably Martin (1997) for the United Kingdom, Baddeley et al. (1998) and the European Commission (2000) for EU member states, Mauro and Spilimbergo (1999) for Spain, Bande et al. (2008) for Spain and other EU member states, and the OECD (2011, 2013) for other countries.

To formally test for cross-sectional dependence, the cross-sectional dependence (CD) test and the local CD test developed by Pesaran (2004, 2015) are applied; the first tests for common factors and the second for spatial dependence. The second test can only be carried out based on a pre-specified matrix W describing the spatial arrangement of the 12 provinces in the sample. The elements of this $N \times N$ matrix are denoted by w_{ij} ($i = 1, \dots, N; j = 1, \dots, N$). For this purpose we adopt a row-normalized binary contiguity matrix, whose elements before normalizing this matrix are set to 1 if two provinces share a

Fig. 3. Geographical distribution of unemployment over time.

common border and zero otherwise. We adopt this matrix since it outperforms alternative specifications to which we come back later in this paper. Pesaran (2015) points out that the CD test works well for T large

and N small, but not for N large and T small, building on previous work of Baltagi et al. (2012). In case of T large, he suggests the standard CD on grounds of its simplicity (p.1099), further supported by Monte Carlo

simulation results of Moscone and Tosetti (2009). The latter two authors also provide an alternative formulation of the local CD test (p. 538), which is easier to understand. Since our sample of $N = 12$ and $T = 41$ best reflects the large T case, we may apply the standard CD tests. In addition to these CD tests, we also apply the exponent of cross-sectional dependence test recently developed by Bailey et al. (2015) to test for the nature of cross-sectional dependence.

The CD test uses the correlation coefficients between the time-series for each panel unit, which for 12 regions results in 12×11 correlations between region r and all other regions, for $r = 1$ to $N - 1$. Denoting these estimated correlation coefficients between the time-series for region r to j as $\hat{\rho}_{rj}$, the Pesaran (2015, eq.1) CD test is defined as $CD = \sqrt{2T/N(N-1)} \sum_{r=1}^{N-1} \sum_{j=r+1}^N \hat{\rho}_{rj}$, where T is the number of observations on each region over the observation period 1973–2013. This test statistic has the limiting $N(0,1)$ distribution as T goes to infinity first, and then N . This implies that the critical values of this two-sided test are -1.96 and 1.96 at the 5% significance level. The local CD test takes the form $\sqrt{T/S} \sum_{r=1}^{N-1} \sum_{j=1}^N w_{rj} \hat{\rho}_{rj}$ (Moscone and Tosetti, 2009, eq.22), where S is the sum of the elements of the spatial weight matrix and thus equal to N^2 .

For our sample of regional unemployment rates, we obtained $CD = 46.31$ and $CD_{local} = 20.38$, and an average pairwise correlation coefficient of 0.901 . These test outcomes are highly statistically significant, corroborating the existence of cross-sectional dependence in regional unemployment rates, which is in line with previous literature (e.g., Molho, 1995; Partridge and Rickman, 1997; Overman and Puga, 2002; Patacchini and Zenou, 2007; Zeilstra and Elhorst, 2014).

To test whether the nature of the found cross-sectional dependence is weak or strong, we also apply the exponent α -test of Bailey et al. (2015).⁷ This test statistic can take values on the interval $(0,1]$; $\alpha \leq 1/2$ points to weak cross-sectional dependence only and $\alpha = 1$ to strong cross-sectional dependence. Values in between indicate moderate to strong cross-sectional dependence and require additional research to discriminate between weak and strong cross-sectional dependence. The test statistic has a limiting $N(0,\omega)$ distribution, where ω depends on the data (see footnote 7). We found $\alpha = 1.008$ with standard error 0.019 . Note that values just above the upper bound of the interval $(0,1)$ are also reported in Table 1 of Bailey et al. (2015), which summarizes the results of their Monte Carlo simulation experiments; such values might occur since not all the asymptotic properties are fully met. However, since the hypothesis $\alpha = 1$ cannot be rejected, we may conclude to have found empirical evidence in favor of at least common factors. Whether spatial dependence also needs to be accounted for will be investigated later.

3. Methodology

An intriguing issue is how to address cross-sectional dependence if potential sources of interactions between regions consists of spatial dependence, due to for example commuting flows (Patacchini and Zenou, 2007), and common factors. Since both sources are likely to be present in applied settings, this issue is receiving increasing attention in the literature (see introduction). To facilitate comparison between the different approaches, we first present the two-stage models, followed by the unified simultaneous model.

3.1. Two-stage models

In the two-stage approach proposed in Bailey et al. (2016), the first stage consists of de-factoring regional unemployment rates, which is viewed as a source of common factors. We model common factors

using cross-sectional averages as proposed by the former authors. Alternatively, they also present modeling common factors using a principal components approach.⁸ The main reason we use the first approach is that it is much better embedded in the economic-theoretical literature on cyclical sensitivity. In fact, the ‘factoring out’ of aggregate cyclical factors has a clear resemblance to Pesaran (2006) and related literature, using cross-unit averages of the variables at each point in time to extract common factors; details are provided in his assumption 5 and remark 3. The corresponding estimator is defined as the common correlated effect estimator and abbreviated to CCE. To highlight the similarity, we explicitly link the latter approach and the basic form of the Brechling-Thirlwall type cyclical sensitivity models, yielding

$$u_{rt} = \gamma_{0r} + \gamma_{1r} \frac{1}{N} \sum_{j=1}^N u_{jt} + e_{rt} \approx \gamma_{0r} + \gamma_{1r} u_{Nt} + e_{rt}, \quad (1)$$

where u_{rt} denotes the unemployment rate for every region $r = 1, \dots, N$ at a particular point in time $t = 1, \dots, T$, and e_{rt} is an independently and identically distributed error term for r and t with zero mean and constant variance σ_e^2 . Further note that instead of one common intercept and one common response coefficient, every region has its own intercept and its own response coefficient.⁹ Being able to account for this heterogeneity is particularly relevant since some regions are most likely to be more sensitive than others to aggregate fluctuations. Three additional remarks apply to this model. First, whereas Pesaran (2006) approaches the cross-sectional average at each point in time by $\frac{1}{N} \sum_{j=1}^N u_{jt}$, the regional cyclical sensitivity literature adopts the national unemployment rate at time t denoted by u_{Nt} . Since the size of the labor force is different in different regions, we have $\frac{1}{N} \sum_{j=1}^N u_{jt} \neq u_{Nt}$, although the difference tends to be small. In remark 3 of his paper, however, Pesaran (2006) leaves room for other weights as long as they satisfy the condition $w_{ij} = O(\frac{1}{N})$. Second, Pesaran (2006) not only considers a cross-unit average of the dependent variable in the model, but also for each of the K explanatory variables. However, just as Bailey et al.'s (2016) study contains no explanatory variables, so does this study. In this sense, both studies are comparable and exactly the same approach is applied, so that when using cross-sectional averages only the dependent variable is left. There is nevertheless one difference, representing the third remark. When moving from a two-stage approach to a unified simultaneous approach, we find that two cross-sectional averages should be considered, namely one at time t and one at time $t - 1$.¹⁰

The de-factored regional unemployment rates are given by the residuals from Eq. (1), as follows

$$\hat{e}_{rt} = u_{rt} - \hat{\gamma}_{0r} - \hat{\gamma}_{1r} u_{Nt}. \quad (2)$$

In this way, common national effects are extracted so that the resulting dependent variable used in the second stage can be seen as being net of aggregate fluctuations. Brechling (1967), in fact, interpreted the residuals as the regional cyclical component. Whereas Blanchard and Katz (1992) use the cyclical sensitivity model to estimate a separate regression for each US state and then take each state's unemployment rate in deviation of the national rate to construct state-specific variables,

⁸ This m -factor model can be seen to be: $u_{rt} = \gamma_{0r} + \sum_{m=1}^M \gamma_{rm} f_m + e_{rt}$; for details refer to their study. We thank an anonymous reviewer for their comment regarding this point. One potential problem discussed in the literature is that it is not always clear how these principal components should be interpreted, as a result of which it can be seen as a statistical device only. By considering the national unemployment rate, we have a common factor which is much easier to interpret and has much more appeal in the literature.

⁹ Thirlwall (1966) first introduced this model formulated in first-differences, and Brechling (1967) in both levels and logarithms. More details can be found in Domazlicky (1980), Martin (1997), and Elhorst (2003).

¹⁰ We demonstrate this shortly. A more minor difference is that in their empirical application on housing prices, Bailey et al. (2016) consider two aggregation levels: the regional level and the MSA level, where each region consists of 45 MSAs, on average. In our study, however, this is not relevant since we have 12 provinces all located in the same country.

⁷ For detailed formulas we refer to Bailey et al. (2015). Gauss code to calculate the CD and the α -tests are made available in an online appendix to their paper.

thereby focusing on common factors only, the de-factoring approach of Bailey et al. (2016) also considers spatial dependence in the second stage.

Thus, we proceed to modeling the de-factored regional unemployment rates using the dynamic spatial panel model

$$\hat{e}_{rt} = \alpha_0 + \alpha_1 \hat{e}_{rt-1} + \alpha_2 \sum_{j=1}^N w_{rj} \hat{e}_{jt} + \alpha_3 \sum_{j=1}^N w_{rj} \hat{e}_{jt-1} + (\mu_r) + (\lambda_t) + \varepsilon_{rt}, \quad (3)$$

where $\hat{e}_{rt}$ is defined as in Eq. (2). The non-negative spatial weights matrix W is usually row-normalized and the diagonal elements are set to zero since no region can be viewed as its own neighbor. α_1 , α_2 , and α_3 are the parameters associated with the lagged dependent variable, the lagged dependent variable in space, and the dependent variable lagged both in space and time, respectively. The first of these three variables is included to address that regional unemployment rates are strongly correlated over time. The other two variables are included to address spatial dependence, where α_2 is referred to as the spatial autoregressive coefficient, and α_3 as the lagged spatial autoregressive coefficient. ε_{rt} is an independently and identically distributed error term for r and t with zero mean and constant variance σ_ε^2 . The model can be extended with regional fixed effects (μ_r) and/or time-period fixed effects (λ_t), which are denoted in parentheses as they are optional; if included, the intercept α_0 is dropped from the model to avoid perfect multicollinearity. Yu et al. (2008) have developed a bias corrected QML estimator for the parameters in Eq. (3) with regional fixed effects, and Lee and Yu (2010b) for the same model with both regional and time fixed effects. It is this estimator which will be used to estimate the parameters of this model.¹¹

Before proceeding with the unified simultaneous approach, it is useful to highlight some differences between model (3) and a basic dynamic spatial panel data model of regional unemployment rates accounting for spatial dependence, which can be seen to be

$$u_{rt} = \alpha_0 + \alpha_1 u_{rt-1} + \alpha_2 \sum_{j=1}^N w_{rj} u_{jt} + \alpha_3 \sum_{j=1}^N w_{rj} u_{jt-1} + (\mu_r) + (\lambda_t) + \varepsilon_{rt}, \quad (4)$$

where all elements are similarly defined as in model (3), but $\hat{e}_{rt}$ is replaced by u_{rt} . Besides this notational difference, another difference is on the methodological issue of whether to include regional and/or time-period effects. They can be crucial in model (4) where it has been shown that if time-period fixed effects are excluded, spatial dependence might be overestimated (Lee and Yu, 2010a), which is corroborated later in the empirical application. This is reasonable since they are meant to control for omitted effects that are common across all units occurring during the observation period. In this respect, time-period fixed effects may partly cover common factors. However, it is important to note this is a homogeneous approach in the sense that it assumes that the impact of these time-period fixed effects is the same across regions, which is not likely to be the case in many applied settings, and also not for our data as we will also show in our empirical application.

In contrast, regional fixed effects and time-period fixed effects may be expected to be insignificant in model (3). The first expectation can be explained by observing that in model (4), the coefficients are homogeneous, whereas in the first stage of the two-stage modeling approach they are not; since the intercept γ_{0r} and the response coefficient γ_{1r} in Eq. (1) are different for different regions in that stage, and their estimated values enter Eq. (3) by $\hat{e}_{rt}$ obtained in Eq. (2), they have the same effect as regional fixed effects in Eq. (4). The explanation of why time-period fixed effects may be expected to be jointly insignificant in model (3) is twofold. First, the development of the national unemployment rate over time reflects the business cycle, which might be an effective substitute for

adding time dummies to the specification. Second, the two-stage model is more flexible. Adding time dummies to Eq. (4) has the effect that all variables are demeaned; for the left-hand side variable of Eq. (4), this transformation takes the form $u_{rt}^* = u_{rt} - \frac{1}{N} \sum_{j=1}^N u_{jt}$, while similar transformations apply to the right-hand side variables. Given that $\frac{1}{N} \sum_{j=1}^N u_{jt} \approx u_{Nt}$ (for example, since the size of the labor force in each region is almost the same in every region), this is equivalent with setting $\gamma_{0r} = 0$ and $\gamma_{1r} = 1$ in the first stage of the de-factoring approach and then estimating Eq. (3) in the second stage based on the corresponding residuals, which is more restrictive than controlling for business cycle effects using the heterogeneous model $\hat{e}_{rt} = u_{rt} - \hat{\gamma}_{0r} - \hat{\gamma}_{0r} u_{Nt}$ with different γ_0 's and γ_1 's for each single region.

Finally, it is to be noted that the common factor approach has similarities with the spatial filtering techniques of Getis and Griffith (2002) in which a variable is first stripped from its embedded spatial dependence. The difference is again in the definition of the weights. In Getis and Griffith (2002), a variable is only stripped for common factors cross-sectional units share with their neighbors to which they are connected according to the specification of the spatial weights matrix (i.e., $w_{rj} > 0$, $r, j = 1, \dots, N$). In Pesaran (2006, remark 3), all units get equal weights of $1/N$, or in this particular case weights proportional to the size of the labor force.

3.2. Simultaneous model

In contrast to the previous approaches, we propose a methodology that simultaneously accounts for spatial dependence and common factors. Bailey et al. (2016, p. 256) touch on this possibility, but do not investigate this. They also doubt whether such a meta approach is possible if W is not specified a priori. We come back to this in Section 4. To demonstrate that this methodology in some way generalizes previous approaches, we first substitute (2) into (3) with $e_{rt} = \hat{e}_{rt}$, leaving out the option in (3) to include regional fixed effects (μ_r) and time-period fixed effects (λ_t) due to their expected insignificance (see the explanation in Section 3.1). This yields

$$(u_{rt} - \gamma_{0r} - \gamma_{1r} u_{Nt}) = \alpha_0 + \alpha_1 (u_{rt-1} - \gamma_{0r} - \gamma_{1r} u_{Nt-1}) + \alpha_2 \sum_{j=1}^N w_{rj} (u_{jt} - \gamma_{0j} - \gamma_{1r} u_{Nt}) + \alpha_3 \sum_{j=1}^N w_{rj} (u_{jt-1} - \gamma_{0j} - \gamma_{1r} u_{Nt-1}) + \varepsilon_{rt}, \quad (5)$$

and after rearranging terms

$$u_{rt} = \alpha_0 + \gamma_{0r} - \alpha_1 \gamma_{0r} - \alpha_2 \sum_{j=1}^N w_{rj} \gamma_{0j} - \alpha_3 \sum_{j=1}^N w_{rj} \gamma_{0j} + \alpha_1 u_{rt-1} + \alpha_2 \sum_{j=1}^N w_{rj} u_{jt} + \alpha_3 \sum_{j=1}^N w_{rj} u_{jt-1} + \gamma_{1r} (1 - \alpha_2) u_{Nt} + \gamma_{1r} (-\alpha_1 - \alpha_3) u_{Nt-1} + \varepsilon_{rt}. \quad (6)$$

The first composite term in the resulting equation is a heterogeneous constant. The other terms show that the regional unemployment rate at time t depends on its serially lagged value, spatially lagged value, and its value lagged both in space and time. In addition, the last two terms show that the regional unemployment rate also depends on the national unemployment rate at times t and $t - 1$ with coefficients $\gamma_{1r}(1 - \alpha_2)$ and $\gamma_{1r}(-\alpha_1 - \alpha_3)$, respectively.¹² This equation can be estimated by

$$u_{rt} = \beta_1 u_{rt-1} + \beta_2 \sum_{j=1}^N w_{rj} u_{jt} + \beta_3 \sum_{j=1}^N w_{rj} u_{jt-1} + \beta_{4r} u_{Nt} + \beta_{5r} u_{Nt-1} + \mu'_r + \varepsilon_{rt} \quad (7)$$

where $\beta_1 = \alpha_1$, $\beta_2 = \alpha_2$, $\beta_3 = \alpha_3$, $\beta_{4r} = \gamma_{1r}(1 - \alpha_2)$, $\beta_{5r} = \gamma_{1r}(-\alpha_1 - \alpha_3)$ and $\mu'_r = \alpha_0 + \gamma_{0r} - \alpha_1 \gamma_{0r} - \alpha_2 \sum_{j=1}^N w_{rj} \gamma_{0j} - \alpha_3 \sum_{j=1}^N w_{rj} \gamma_{0j}$. In this

¹¹ This quasi ML estimator does not produce heteroskedastic-robust standard errors, but does not require the normality assumption.

¹² Note that $\sum_{j=1}^N w_{rj} u_{Nt} = u_{Nt}$, provided that W is row-normalized.

equation the first three coefficients are the same for all regions, while the next two coefficients are different for different regions. By not imposing the restriction $\beta_{4r}/(1 - \alpha_2) = \beta_{5r}/(-\alpha_1 - \alpha_3)$ for $r = 1, \dots, N$ in (7), related to the fact that u_{Nt} and u_{Nt-1} share the same coefficient γ_{1r} in (6), the simultaneous approach becomes more general than the two-stage approach set out in Section 3.1. The intercept also appears to be different for different regions in the sample, which can be captured by controlling for regional fixed effects. There is no indication that we should also account for time-period fixed effects. Furthermore, if time-period fixed effects would be added to Eq. (7), the national unemployment rates for different regions at times t and $t - 1$ need to be removed due to perfect multicollinearity.

From Eq. (7) in combination with Eq. (6) it can be seen that all previous models are special cases. Eq. (4), representing the spatial panel data model without common factors, can be obtained by imposing the restrictions $\gamma_{1r} = 0$ for $r = 1, \dots, N$ in Eq. (6), which is equivalent to $\beta_{4r} = \beta_{5r} = 0$ in Eq. (7), provided that Eq. (4) does not contain time-period fixed effects. This condition is important since the inclusion of time-period fixed effects in Eq. (4) can partly (but not fully) mitigate the effects of omitting the national unemployment rate from the model, as pointed out in Section 3.1. Eq. (1), representing the common factor model or the cyclical sensitivity model without spatial dependence, can be obtained by imposing the restrictions $\alpha_0 = \alpha_1 = \alpha_2 = \alpha_3 = 0$ in Eq. (6), or $\beta_1 = \beta_2 = \beta_3 = 0$ in Eq. (7). Finally, the two-stage model in Eqs. (2) and (3) of Bailey et al. (2016) can be obtained from imposing the restriction $\beta_{4r}/(1 - \alpha_2) = \beta_{5r}/(-\alpha_1 - \alpha_3)$ for $r = 1, \dots, N$ in Eq. (7).

4. Results

First, we start with the basic dynamic spatial panel data model (4) estimation results reported in Table 2, Panel A. Given the empirical evidence in favor of common factors in addition to spatial dependence based on the α -test, the results may be expected to be biased. The interesting question is to which extent. In column (1) we control for regional fixed effects, and in column (2) for both regional and time-period fixed effects. Throughout this section we use the likelihood ratio (LR) test to test different model specifications against each other. The LR test is based on minus two times the difference between the value of the log-likelihood function in the restricted model and the value of the log-likelihood function of the unrestricted model: $-2 * (\ln L_{\text{restricted}} - \ln L_{\text{unrestricted}})$. This test statistic has a chi-squared distribution with degrees of freedom equal to the number of restrictions imposed. The results to investigate the (null) hypothesis that the time-period fixed effects are jointly insignificant and thus can be replaced by one common intercept (224.7, with 40 degrees of freedom [df], $p = 0.00$) indicate

Table 2
Serial dynamics and spatial dependence.

	Panel A		Panel B		
	(1)	(2)	(3)	(4)	(5)
α_0			0.001 (0.024)		
α_1	0.679 (0.039)	0.716 (0.037)	0.643 (0.036)	0.687 (0.038)	0.689 (0.040)
α_2	0.756 (0.025)	0.252 (0.073)	0.147 (0.057)	0.154 (0.058)	0.240 (0.074)
α_3	−0.460 (0.047)	−0.002 (−0.038)	0.054 (0.081)	0.058 (0.093)	0.083 (0.124)
Regional fixed effects	Yes	Yes	No	Yes	Yes
Time-period fixed effects	No	Yes	No	No	Yes
R^2	0.942	0.955	0.455	0.456	0.494
Log-likelihood	−481.3	−368.9	−379.8	−379.2	−359.5

Notes: Standard errors are reported in parentheses; Panel A reports the dynamic spatial panel data model results, while Panel B reports the de-factored (second-stage) model results; except for column (3), the bias corrected ML estimator of Lee and Yu (2010b) is applied for models containing time-period fixed effects, and of Yu et al. (2008) for models without time-period fixed effects.

Table 3
Common factors.

	γ_{0r}		γ_{1r}	
Groningen	−0.069	(0.377)	1.362	(0.058)
Friesland	−1.418	(0.377)	1.341	(0.058)
Drenthe	0.004	(0.377)	1.160	(0.058)
Overijssel	−0.819	(0.377)	1.208	(0.058)
Flevoland	0.284	(0.377)	1.098	(0.058)
Gelderland	−0.940	(0.377)	1.108	(0.058)
Utrecht	−0.788	(0.377)	0.914	(0.058)
North-Holland	−0.781	(0.377)	1.063	(0.058)
South-Holland	−0.200	(0.377)	0.945	(0.058)
Zeeland	0.026	(0.377)	0.842	(0.058)
North-Brabant	−0.974	(0.377)	1.119	(0.058)
Limburg	0.603	(0.377)	1.011	(0.058)
R^2	0.918			
Log-likelihood	−537.0			

Note: Standard errors are reported in parentheses.

that this hypothesis must be rejected. Similarly, the hypothesis that the regional fixed effects are jointly insignificant must be rejected (50.8, 11 df, $p = 0.00$), where it should be noted that the estimation results for the model with time-period fixed effects only are not reported. These test results justify the extension of Eq. (4) with both regional and time-period fixed effects.

As can be seen in the first column, the serially lagged unemployment rate (α_1) comes out to be highly significant, reflecting the strong correlation in regional unemployment rates over time observed earlier. In addition, the spatial autoregressive coefficient (α_2) appears to be positive and highly significant 0.756 (0.025), and the lagged spatial autoregressive coefficient (α_3) to be negative and highly significant -0.460 (0.047). However, if time-period fixed effects are controlled for, the spatial autoregressive coefficient estimate is much lower with a value of 0.252 (0.073), while the lagged spatial autoregressive coefficient decreases considerably in magnitude and becomes insignificant. This confirms the importance of including time-period fixed effects to partly cover for the fact that regional unemployment rates tend to increase and decrease together along the national evolution of this variable over time. It also corroborates Lee and Yu's (2010a) finding that if this common effect is not taken into account and therefore not separated out from the local spatial interaction effects among the regions, the latter may be severely overestimated as is clearly shown by the numbers above. However, the impact of this common effect is assumed to be the same across regions, $\gamma_{1r} = 1$ for $r = 1, \dots, N$, which is not realistic, especially considering the regional cyclical sensitivity and the common factor literature. This also follows from the CD and α tests applied to the residuals of this model: $CD = 2.052$, $CD_{\text{local}} = 0.812$, and $\alpha = 0.722$ with standard error 0.076. Local spatial dependence appears to be effectively covered, but the CD test still provides evidence in favor of common factors, while the α -test, despite its decrease, still points to moderate cross-sectional dependence.

We thus proceed to the estimation results of the Brechling-Thirlwall type cyclical sensitivity model (1), with results presented in Table 3.¹³ The log-likelihood function value of this model amounts to -537.0 . It falls to -550.1 when this model is re-estimated imposing one common intercept for each region, to -577.0 when imposing one common response coefficient for each region, and to -800.1 when imposing one common intercept and one common response coefficient for each region. All these restrictions are rejected based on the corresponding LR tests.¹⁴ This result that regions differ in their elasticity to common

¹³ The standard errors of γ_{0r} and γ_{1r} are obtained by taking the square root of the diagonal elements of the 2×2 variance-covariance matrix $\sigma^2(X'X)^{-1}$, where $X = [u_r \ u_N]$ and u_r is a $T \times 1$ vector of ones. Since X is the same for every region, so are these standard errors.

¹⁴ The LR tests amount to 26.3 (11 df, $p = 0.01$), 80.1 (11 df, $p = 0.00$), and 526.2 (22 df, $p = 0.00$), respectively.

shocks (the last column of Table 2) is in accordance with the observations discussed in Section 2; despite a shared link between the regional rates and the national rate in the overall temporal pattern, regional heterogeneity was apparent from visualizing unemployment trends in Figs. 1 and 3. The traditional interpretation of the parameter γ_{1r} is that it measures cyclical sensitivity, i.e. the sensitivity of regional unemployment to aggregate fluctuations. If the estimate is greater than one, this gives an indication that the region is cyclically sensitive, whereas if it is less than one then it is not. From this interpretation, it appears that the most cyclically sensitive regions are Groningen and Friesland, followed by Overijssel and Drenthe, which are all provinces located in the northern part of the country.¹⁵

At the other end of the spectrum are Zeeland, Utrecht, and South-Holland, with the latter province neighboring the former two. The other provinces fall between with estimates greater than one, but not as large in size as those mentioned previously. There is the issue, however, whether this is a satisfactory measure of cyclical sensitivity. This parameter may also reflect long-lasting problems such as structural unemployment in relation to the rest of the country; in this respect, regions with estimates greater than one also tend to be those with unemployment rates that are persistently above the national average irrespective of the phase of the business cycle (Brechtling, 1967; Domazlicky, 1980). To capture the influence of long-term disadvantage, the former study includes a time trend, but also includes seasonal dummy terms. Interestingly, we find that when the simultaneous approach is applied, results change considerably, which we come back to shortly. The reason not to stop here but to also consider spatial dependence again follows from the CD and α tests applied to the residuals of this common factor model: $CD = 1.459$, $CD_{local} = 4.263$, and $\alpha = 0.584$ with standard error 0.090. According to the decline in the CD and the α test statistics, common factors have been effectively factored out. However, the local CD statistics still provides evidence in favor of local spatial dependence, and so does the α test statistic, although to a limited extent.

To account for both spatial dependence and common factors, we now move forward to the two-stage approach. First, we obtain the residuals as shown in Eq. (2), using the parameter estimates reported in Table 3, and then model these de-factored regional unemployment rates using the dynamic spatial panel specification (3), with the estimation results reported in Table 2, Panel B. The first column of results (column 3 in the table) is the base model which does not include regional fixed effects and time-period fixed effects. The specification in the next column includes regional fixed effects, while the last column reports results where both effects are included. As expected, the regional and time-period fixed effects appear to be jointly insignificant in the second stage of the de-factoring approach. The LR test results whether the regional fixed effects are jointly insignificant amounts to 1.1 (11 df, $p = 0.99$) and whether the time-period fixed effects are jointly insignificant to 39.6 (40 df, $p = 0.49$). The reason is that the regional fixed effects and time-period fixed effects are already covered in the first stage of the two-stage modeling procedure. Moreover, the latter specification (column 5 in the table) even comes out to be non-stationary, that is, $\alpha_1 + \alpha_2 + \alpha_3 > 1$.

It can be observed that the results across these three columns of Panel B are quite similar, with an exception being the spatial autoregressive coefficient estimate (α_2), which is somewhat larger both in terms of the magnitude and significance in the last column of Table 2, but this model is rejected and unstable. The lagged spatial autoregressive coefficient (α_3) remains almost the same, with a low magnitude of around 0.05 and is statistically insignificant across all of these three specifications. By contrast, the temporal effect (α_1) is large and significant in every specification. It is important to stress that even after de-factoring and controlling for both regional and time-period fixed effects, either in the first stage or both in the first and the second stage of the de-factoring approach

(successively, panels B and A in Table 2), the estimate of the contemporaneous spatial interaction effect (α_2) remains positive and significant. This outcome suggests that spatial dependence is of crucial importance in the context of regional unemployment rates, even when serial dynamics and common factors have been accounted for.

It is also interesting to compare Panels A and B. The results in the first column of Panel A confirm that, indeed, estimating a spatial model without accounting for the existence of common factors leads to biased inference, which is the point stressed in Bailey et al. (2016). However, the results from the second column of Panel A with controls for regional and time period fixed effects are not that much different from those in Panel B. This outcome is understandable since these are two different approaches that deal with the same problem of region-invariant unobserved differences among time periods. On the other hand, the parameter estimates do differ, indicating that controls for time period fixed effects are nonetheless more restrictive than the de-factoring approach since the impact of the common effect is heterogeneous.

In contrast to this aforementioned resemblance, we find that using the simultaneous approach to serial dynamics, spatial dependence, and common factors shifts results considerably, especially pertaining to the estimates of the region-specific cyclical sensitivity parameter γ_{1r} and the spatial autoregressive coefficient α_2 . These results from estimating Eq. (7) are shown in Table 4.¹⁶ Regional fixed effects have been added to allow the intercept to be different for different regions, in line with the argument below Eq. (7) that the intercept is different for different regions, despite the fact that the hypothesis whether these regional fixed effects are jointly insignificant cannot be rejected (LR-test: 16.5, 11 df, $p = 0.12$). Time-period fixed effects have not been added as they are already covered by simultaneously accounting for common factors and would be perfectly multicollinear with the national unemployment variables. When considering the CD test statistics of the two-stage and of the simultaneous model approaches on their residuals, both appear to have effectively covered spatial dependence and common factors; in case of the two-stage approach we obtained $CD = -0.670$ and $CD_{local} = 0.454$, and in case of the simultaneous approach $CD = -0.020$ and $CD_{local} = -1.034$. The question that remains is whether the simultaneous model outperforms the two-stage approach.

For this purpose, additional calculations are needed to compare the γ_{1r} estimates with their counterparts from Eq. (1) using the two-stage approach. Table 4 contains two columns reporting the results: one if γ_{1r} is calculated by $\beta_{4r}/(1 - \alpha_2)$, where β_{4r} is the coefficient estimate of u_{Nr} in Table 4, and one if γ_{1r} is calculated by $\beta_{5r}/(-\alpha_1 - \alpha_3)$, where β_{5r} is the coefficient estimate of u_{Nr-1} in Table 4. The standard errors are calculated using formulas for the sum and quotient of random variables (see, among others, Mood et al., 1974, pp. 178–181). An LR test whether these 12 coefficients in both columns are the same (cf. Eq. (6)) can be based on the log-likelihood function value of the simultaneous model in Table 4 (−362.3) and that of the two-stage model including regional fixed effects (−379.2) in Table 2. This yields 33.9 with 12 df and $p = 0.00$, indicating that the two-stage model needs to be rejected in favor of the simultaneous model and that the national rate has a different impact on the provinces in time t compared to $t - 1$.

Large differences emerge for the γ_{1r} estimates (strong cross-sectional dependence). To exemplify the biases we focus on the provinces of Groningen and North-Brabant, and compare the last column of Table 3 with the last column in Table 4. We use the last rather than the second last column of Table 4, that is, we focus on the coefficient estimates of u_{Nr-1} rather than u_{Nr} , since these coefficients in terms of their corresponding standard errors appear to be more reliable. According to the two-stage approach the impact of the national unemployment rate is strongest for Groningen with 1.362, while the elasticity amounts to 1.119 for North-Brabant. According to the simultaneous

¹⁵ Overijssel is officially part of the Eastern Netherlands, but is a neighbor of Friesland and Drenthe, which together with Groningen form part of the Northern Netherlands.

¹⁶ Recall that $\beta_1 = \alpha_1$, $\beta_2 = \alpha_2$, $\beta_3 = \alpha_3$.

Table 4

Simultaneous approach to serial dynamics, spatial dependence and common factors.

Common factors	β_{4r}		B_{5r}		$\beta_{4r}/(1 - \alpha_2)$		$B_{5r}/(-\alpha_1 - \alpha_3)$	
Groningen	0.913	(0.114)	−0.675	(0.152)	1.034	(0.169)	0.910	(0.054)
Friesland	0.986	(0.112)	−0.736	(0.143)	1.118	(0.157)	0.991	(0.045)
Drenthe	1.020	(0.113)	−0.906	(0.145)	1.155	(0.156)	1.221	(0.035)
Overijssel	1.092	(0.111)	−0.919	(0.134)	1.237	(0.146)	1.238	(0.032)
Flevoland	0.925	(0.108)	−0.824	(0.131)	1.048	(0.162)	1.111	(0.035)
Gelderland	0.881	(0.109)	−0.726	(0.127)	0.998	(0.168)	0.978	(0.040)
Utrecht	0.696	(0.107)	−0.590	(0.128)	0.789	(0.196)	0.794	(0.054)
North-Holland	0.814	(0.108)	−0.636	(0.132)	0.922	(0.174)	0.857	(0.050)
South-Holland	0.764	(0.108)	−0.628	(0.126)	0.866	(0.181)	0.846	(0.048)
Zeeland	0.637	(0.111)	−0.550	(0.127)	0.722	(0.215)	0.740	(0.059)
North-Brabant	1.079	(0.106)	−0.949	(0.123)	1.223	(0.142)	1.279	(0.028)
Limburg	0.926	(0.113)	−0.839	(0.126)	1.050	(0.166)	1.130	(0.033)
<i>Serial dynamics</i>								
α_1	0.664	(0.038)						
<i>Spatial dependence</i>								
α_2	0.118	(0.059)						
α_3	0.079	(0.082)						
R^2	0.956							
Log-likelihood	−362.3							

Notes: Standard errors are reported in parentheses; regional fixed effects included. The bias corrected ML estimator developed in Yu et al. (2008) is applied. As noted in the main text, a direct comparison with Table 3 requires further calculations, which are reported in the last two columns.

approach, we obtain 0.910 for Groningen and 1.279 for North-Brabant. Groningen is therefore less cyclically sensitive, while North-Brabant is more sensitive. A similar result as for Groningen is found for its neighboring province of Friesland. This change may reflect that the Northern provinces, such as Groningen and Friesland, suffer more from long-standing disadvantage relative to the nation, such as structural unemployment, than the results of the two-stage approach suggest. One explanation that North-Brabant is found to be more sensitive is that this province has a relatively high share of employment in manufacturing and is one of the most export-oriented provinces in the Netherlands; therefore, it is much more dependent on the economic development of the European and world economy. Finally, the estimate of the contemporaneous spatial interaction effect with neighboring regions falls from 0.252 when ignoring common factors, to 0.147 when using the two-stage approach, and eventually to 0.118 when accounting for both spatial dependence and common factors simultaneously.

Our results demonstrate that sequential approaches as applied in Blanchard and Katz (1992), Decressin and Fatás (1995), Getis and Griffith (2002), Badinger et al. (2004), and Bailey et al. (2016) run the risk of obtaining biased results. In Blanchard and Katz (1992) and Decressin and Fatás (1995) a Brechling-Thirlwall type model is estimated in the first stage to divide the regional unemployment rate into a short-term and long-term component net of cyclical factors, and then in the second modeling stage the long-term component is estimated for all regions taken together. However, it is more likely that these two types of dynamics are interdependent since short-term dynamics may have major long-run structural impacts and, conversely, structural changes may change the short-run dynamics of regional economies.

Getis and Griffith (2002) and Badinger et al. (2004) convert variables that are spatially autocorrelated (local spatial dependence) into spatially independent variables in the first stage, and then, conditional upon these spatially filtered variables, conventional regression models are run, among which are models accounting for serial dynamics. However, it is more likely that serial dynamics and spatial autocorrelation affect each other. For example, LeSage and Pace (2009, ch. 7) show that a process with high temporal dependence and low spatial dependence might nonetheless imply a long-run equilibrium with high spatial dependence.

A similar argument applies to the common factor approach of Bailey et al. (2016) and related literature, which propose a separation of two model stages: first, accounting for common factors and second,

accounting for spatial dependence. However, it is more likely that both forms of cross-sectional dependence are interdependent. The mutual structure of regions may have major structural impacts of the national economy on that of its regions, while these impacts in their turn may affect the relationships among regions.

By merging and simultaneously accounting for dynamics, spatial dependence and common factors, our proposed methodology in some aspects generalizes previous approaches and creates more flexibility. The finding that the residuals obtained from the first-stage regression of the two-stage approach may be biased (due to biases in the γ parameters) also throws another light on the idea put forward in Bailey et al. (2016) to estimate the matrix of connections, in the spatial econometrics literature known as the spatial weight matrix W , based on these residuals. If these residuals are biased, so will be the spatial weight matrix and thus the parameter estimates in the second stage. A better idea is to alternately estimate the simultaneous model, given W , on the one hand and W based on the residuals using Eq. (2), given the parameter estimates of the simultaneous model, on the other hand. Whether this idea of an iterative two-step procedure also converges, needs to be further investigated.

A potential objection might be that our results are conditional on the row-normalized first-order binary contiguity matrix. For this reason, we also considered alternative specifications of the spatial weight matrix, to begin with a second-order binary contiguity matrix since for example, commuters can pass through more than one province. However, the main conclusions remain the same, while the log-likelihood function value of the simultaneous model of −363.4 when adopting this matrix is lower than that of its first-order counterpart reported in Table 4. This result is in line with a previous study of Halleck Vega and Elhorst (2014), who investigated the performance of ten different specifications of W , including matrices based on geographical variables only, on economic variables only, and on combinations of these variables when explaining unemployment, labor force participation and employment growth in 112 regions across 8 EU countries (among which the 12 provinces in the Netherlands) over the period 1986–2010. They found that the model probabilities of the first and second-order binary contiguity matrices (limited to interaction effects across regions within countries) in the explanation of unemployment take values of 0.655 and 0.345 respectively, and that the probabilities of all other matrices are 0.000. For this reason, we mainly focused on these two binary contiguity matrices. However, to be sure that similar results also hold for this

study, we also consider three additional specifications, one based on population ratios ($w_{ij} = POP_j / POP_r$), one based on inverse distances between each pair of regions ($w_{ij} = 1/d_{ij}$), and one based on the combination ($w_{ij} = (POP_j / POP_r) / d_{ij}$), where population sizes observed at the start of the sample period are used. As expected, the log-likelihood function values of the simultaneous model when adopting these matrices are also lower (−362.8, −364.0 and −363.7, respectively).

A final and interesting issue arising from Eq. (7) is the decomposition of the regional unemployment rate into the influence of regional and national factors, i.e., spatially lagged variables and common factors, respectively. To assess the relative contribution of these factors in explaining regional unemployment rates, we use the Shapley-based decomposition of the R^2 (Israeli, 2007). A critical issue here is the method used to determine the R^2 values, since there is discussion in the literature about whether or not fixed effects should be included in this measurement and whether the endogenous spatial lag in the dependent variable ($\sum_{j=1}^N w_{ij} u_{jt}$) should be treated as a right-hand side variable or whether the reduced-form equation should be considered, which treats $\sum_{j=1}^N w_{ij} u_{jt}$ as a left-hand side variable. A more detailed discussion can be found in Elhorst (2014, Section 3.5.1).

In the comparison below, the dependent variable lagged in time and the regional fixed effects are considered to be part of every model. Since common factors, if included, are treated as right-hand side variables, so is the endogenous spatial lag in the dependent variable; otherwise the model without common factors and the model without spatially lagged variables are not comparable. Time-period fixed effects are left out in any of the models when determining the R^2 . Since they are replaced by common factors model for reasons explained in Section 3.3, and thus may be seen as a kind of common or national factor in the model of spatial dependence introduced in Section 3.1, they should not be treated as a regional factor. Starting from these principles, we obtain the R^2 values from estimating the full model with both regional and national factors in Table 4 ($R^2_{full} = 0.956$), the model without national factors in column (1) of Table 2 ($R^2_{reg} = 0.942$), the model without regional factors ($R^2_{nat} = 0.955$), and finally the model with no regional or national factors ($R^2_{no} = 0.814$). Since the last two models have not been reported in this study, these values have been determined separately.

The absolute contributions can then be determined, with the regional contribution being $\frac{1}{2}[(R^2_{full} - R^2_{nat}) + (R^2_{reg} - R^2_{no})]$, and the national contribution $\frac{1}{2}[(R^2_{full} - R^2_{reg}) + (R^2_{nat} - R^2_{no})]$, which are 0.0645 and 0.0775, respectively. To obtain the relative contributions, these values are divided by their sum, giving 45.4% and 54.6% for respectively the regional and national factors (cf. Zeilstra and Elhorst, 2014). Overall, the results suggest that these factors are almost equally important.

5. Conclusion

In the context of explaining regional unemployment, previous literature has accounted for serial dynamics in combination with either spatial dependence or common factors, also viewed as respectively, weak and strong cross-sectional dependence in the literature. Recently, there is increased attention on a methodology enabling to address both forms of cross-sectional dependence. Joining serial dynamics, spatial dependence and common factors has recently been applied in the context of house prices (see e.g., Bailey et al. 2016) using a two-stage modeling approach. Although such a sequential approach can be seen as an important step trying to deal with these different dynamics, separating the stages can potentially lead to biased results since serial dynamics, spatial dependence and common factors are more likely to be interdependent.

In this paper we propose a regional unemployment model simultaneously accounting for serial dynamics, spatial dependence and common factors. As an application, we investigate the regional evolution of unemployment differentials in the Netherlands. The empirical results are illuminating as they demonstrate that applications based

on sequential approaches, such as two-step procedures consisting of first de-factoring observations and then applying spatial econometric techniques, run the risk of obtaining biased results. In this respect, in many applied settings, it is not only relevant to account for common factors and spatial dependence (and serial effects), but also to appraise the potential consequences of accounting for these effects simultaneously instead of separately. A further way forward would be to also include explanatory variables in the model.

As a final thought, the terminology of weak and strong cross-sectional dependence commonly used in the literature is to some extent misleading. Strong is used in reference to common shocks being pervasive by nature, whereas weak is used in reference to spatial interactions between units being localized in character (cf. Bailey et al. 2016). However, the terms strong and weak suggest that the former is more important than the latter, while we find that their contributions are almost equally as important. From now on we therefore propose the descriptions common factors and spatial dependence to acknowledge the importance of both properties.

References

- Anselin, L., 1988. *Spatial Econometrics: Methods and Models*. Kluwer, Dordrecht.
- Baddeley, M., Martin, R., Tyler, P., 1998. European regional unemployment disparities: convergence or persistence? *Eur. Urban Reg. Stud.* 5, 195–215.
- Badinger, H., Müller, W.G., Tondl, G., 2004. Regional convergence in the European Union (1985–1999): a spatial dynamic panel analysis. *Reg. Stud.* 38, 241–253.
- Bailey, N., Kapetanios, G., Pesaran, M.H., 2015. Exponent of cross-sectional dependence: estimation and inference. *J. Appl. Econ.* <http://dx.doi.org/10.1002/jae.2476>.
- Bailey, N., Holly, S., Pesaran, M.H., 2016. A two-stage approach to spatio-temporal analysis with strong and weak cross-sectional dependence. *J. Appl. Econ.* 31, 249–280.
- Baltagi, B.H., Feng, Q., Kao, C., 2012. A Lagrange multiplier test for cross-sectional dependence in a fixed effects panel data model. *J. Econ.* 170, 164–177.
- Bande, R., Fernandez, M., Montuenga, V., 2008. Regional unemployment in Spain: disparities, business cycle and wage setting. *Labour Econ.* 15, 885–914.
- Blanchard, O.J., Katz, L.F., 1992. Regional evolutions. *Brook. Pap. Econ. Act.* 1, 1–75.
- Brechling, F., 1967. Trends and cycles in British regional unemployment. *Oxf. Econ. Pap.* 19, 1–21.
- Burridge, P., Gordon, I., 1981. Unemployment in the British metropolitan labour areas. *Oxf. Econ. Pap.* 33, 274–297.
- Chudik, A., Pesaran, M.H., Tosetti, E., 2011. Weak and strong cross-section dependence and estimation of large panels. *Econ. J.* 14, C45–C90.
- Decressin, J., Fatás, A., 1995. Regional labor market dynamics in Europe. *Eur. Econ. Rev.* 39, 1627–1655.
- Domazlicky, B., 1980. Regional business cycles: a survey. *Reg. Sci. Perspect.* 10, 15–34.
- Elhorst, J.P., 1995. Unemployment disparities between regions in the European Union. In: Armstrong, H.W., Vickerman, R.W. (Eds.), *Convergence and Divergence Among European Regions*. Pion, London, pp. 190–200.
- Elhorst, J.P., 2003. The mystery of regional unemployment differentials: theoretical and empirical explanations. *J. Econ. Surv.* 17, 709–748.
- Elhorst, J.P., 2014. *Spatial Econometrics: From Cross-Sectional Data to Spatial Panels*. Springer, Heidelberg, New York, Dordrecht, London.
- European Commission, 2000. Sixth Periodic Report on the Social and Economic Situation and Development of Regions in the European Union. European Commission, Brussels.
- Eurostat, 2014. *Eurostat Regional Yearbook*. Eurostat, Luxembourg.
- Getis, A., Griffith, D.A., 2002. Comparative spatial filtering in regression analysis. *Geogr. Anal.* 34, 130–140.
- Halleck Vega, S., Elhorst, J.P., 2014. Modelling regional labour market dynamics in space and time. *Pap. Reg. Sci.* 93, 819–841.
- Hyclak, T., 1996. Structural changes in labor demand and unemployment in local labor markets. *J. Reg. Sci.* 36, 653–663.
- Holly, S., Pesaran, M.H., Yamagata, T., 2010. A spatio-temporal model of house prices in the USA. *J. Econ.* 158, 160–173.
- Holly, S., Pesaran, M.H., Yamagata, T., 2011. The spatial and temporal diffusion of house prices in the UK. *J. Urban Econ.* 69, 2–23.
- Israeli, O., 2007. A Shapley-based decomposition of the R-square of a linear regression. *J. Inequal.* 5, 199–212.
- Kuersteiner, G.M., Prucha, I.R., 2015. *Dynamic Spatial Panel Models: Networks, Common Shocks, and Sequential Exogeneity*. University of Maryland, Working paper.
- Lee, L.-F., Yu, J., 2010a. Some recent developments in spatial panel data models. *Reg. Sci. Urban Econ.* 40 (5), 255–271.
- Lee, L.-F., Yu, J., 2010b. A spatial dynamic panel data model with both time and individual fixed effects. *Econ. Theor.* 26, 564–597.
- LeSage, J.P., Pace, R.K., 2009. *Introduction to Spatial Econometrics*. Taylor and Francis, Boca Raton, FL.
- Martin, R.L., 1997. Regional unemployment disparities and their dynamics. *Reg. Stud.* 31 (3), 237–252.
- Mauro, P., Spilimbergo, A., 1999. Regional labor markets in Spain. In: Mauro, P., Prasad, E., Spilimbergo, A. (Eds.), *Perspectives on Regional Unemployment in Europe*. International Monetary Fund, Washington DC, pp. 29–41.

- Mood, A.M., Graybill, F., Boes, D.C., 1974. *Introduction to the Theory of Statistics*. third ed. McGraw-Hill, Tokyo.
- Molho, I., 1995. Spatial autocorrelation in British unemployment. *J. Reg. Sci.* 35 (4), 641–658.
- Moscone, F., Tosetti, E., 2009. A review and comparison of tests of cross-section independence in panels. *J. Econ. Surv.* 23 (2), 528–561.
- OECD, 2011, 2013. *Regions at a Glance*. OECD Publishing, Paris.
- Overman, H.G., Puga, D., 2002. Regional unemployment clusters: nearness matters within and across Europe's borders. *Econ. Policy* 17 (34), 115–148.
- Partridge, M.D., Rickman, D.S., 1997. The dispersion of US state unemployment rates: the role of market and non-market equilibrium factors. *Reg. Stud.* 31 (6), 593–606.
- Patacchini, E., Zenou, Y., 2007. Spatial dependence in local unemployment rates. *J. Econ. Geogr.* 72 (2), 169–191.
- Pesaran, M.H., 2004. General diagnostic tests for cross section dependence in panels. CESifo Working Paper Series No. 1229 (Available at SSRN: <http://ssrn.com/abstract=572504>).
- Pesaran, M.H., 2006. Estimation and inference in large heterogeneous panels with a multifactor error structure. *Econometrica* 74 (4), 967–1012.
- Pesaran, M.H., 2015. Testing weak cross-sectional dependence in large panels. *Econ. Rev.* 34 (6–10), 1088–1116.
- Thirlwall, A.P., 1966. Regional unemployment as a cyclical phenomenon. *Scott. J. Polit. Econ.* 13, 205–219.
- Yu, J., de Jong, R., Lee, L.-F., 2008. Quasi-maximum likelihood estimators for spatial dynamic panel data with fixed effects when both n and T are large. *J. Econ.* 146, 118–134.
- Zeilstra, A., Elhorst, J.P., 2014. Integrated analysis of regional and national unemployment differentials in the European Union. *Reg. Stud.* 48 (10), 1739–1755.