Changing relationships. An application to the Polish case

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Motivation and goals

It is usual in the spatial econometric literature to treat the weighting matrix, W, as fixed apriori. It is also widely accepted that this is unsatisfactory, and so researchers often report informal attempts to test the effects of this assumption, for example by considering several alternative versions of W and then comparing the results (see, for instance, Debarsy et al., 2016, among many others). Extending this reasoning a bit further, we can also cite the study of Javan rice farm efficiency of Druska and Horrace (2004) where they conclude that their two seasons model needed two different pre-specied weighting matrices, one for the dry season, the other for the wet season; similarly, the case of Case et al. (1993) where the authors advocate for a (flexible) weighting matrix, obtained as a linear combination of two original matrices, $W = \lambda W_a + (1 - \lambda)W_b$, for modelling budget spillovers across states. The nuisance linear parameter λ is estimated from the data.

There is also a lot of work that approached the problem from a methological perspective such as Florax and Rey (1995) or Griffith and Lagona (1998) which, first, consider a misspecified W matrix and then they study experimentally its impact on usual statistical inference. Recently, Lee and Yu (2012) develop a quasi-maximum likelihood estimation, QML, of dynamic panel data models where spatial weights matrices are also time-varying, which are assumed to be exogeneous and known. QML estimates are consistent and asymptotically normal when both the number of spatial units and time periods increase. More important for us, Lee and Yu also detect signicant biases in the case of substantial misspecication, with a time invariant weighting matrix assumed when the true process has time varying matrices. The magnitude of the bias increases for the estimates of the marginal direct/indirect effects.

To complete the picture, let us mention the work of Bhattacharjee and Jensen-Butler (2013) and Ahrens and Bhattacharjee (2015) developping consistent algorithms to estimate an unknown W matrix

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from a panel data set, whereas Lee and Yu (2012) consider also estimation problems in the presence of an exogenously given sequence of known weights matrices. Kelejian and Piras (2014) and Qu and Lee (2015) made signicant advances in the treatment of endogenous weighting matrices, also in a panel framework. For the case of a single period, Benjanuvatra and Burridge (2015) introduce a consistent procedure to estimate from the data, and using quasi-maximum likelihood methods, a fully parametrized W weighting matrix. Angulo et al. (2017a) extend their work to a panel framework, which includes a variant of the Andrews (1993) test for structural change to locate, in time, unknown breakpoints in the network of cross-sectional interaction of the sample.

Given this background, the purpose of our paper is to carry out an in-depth analysis of the cross-sectional relationships existing in the Polish labour market. To that end, we are going to use the main layers of the Polish territorial administration: voivodeships, or provinces, and powiats, or counties. The analysis is going to be focused on the short-run dynamics of the spatial relations using, when possible, high frecuency series. Our main concern is to check for the stability of the spatial structure across time. We do expect to find evidence of several breakpoints, related to exceptional shocks suffered by this economy in the last decades. If we corroborate this assumption, the next stage is to evaluate the importance of the changes, for which it will be necessary to model the cross-sectional relationships that prevailed before and after the shocks. This information would allows us to characterize the spatial pattern of the changes and fo formulate some hypotheses about their generation and launching mechanism.

Techniques and methods

There are several technical aspects of crucial importance to put forward our analysis. They are the followings:

- Testing for breaks in the weighting matrix. There are not too many results available in the literature but Angulo et al. (2017b) present a set of tests, developped in the context of multivariate analysis, whose aim is to check for breaks in the covariances matrix of a dataset. Given the close relationship that exists, in a spatial model, between weighting matrix and the covariance matrix these tests, as shown by the authors, are useful to detect and locate unknown breakpoints. Moreover, this approach will be combined with that of Angulo et al (2017a), which requieres a more formal parametrization of the spatial weights using power or exponencial functions of the distance between the centroids of the spatial units. Finally, Carrion et al. (2015), from a purely time series perspective, develop a panel unit root test robust to stuctural breaks of a general type that, simultaneously, identifies the breakpoints present in the sample. Our intention is to compare the result obtained with the three approaches applied to the Polish case.

- After detecting and characterizing the breakpoints, the next step is to built the weighting matrices corresponding to each period. At this point we are going to use three differente techniques. First is the QMLE approach of Angulo et al. (2017a) which, as said, requires a fully parameterized weighting matrix with respect to the geographical distance. The second is the two-step Lasso algorithm of Ahrens and Bhattacharjee (2015) directed to circumvent endogeneity problems associated with the spatial lags of the endogenous variable in autorregressive panel data models.

Finally, there is the approach of Battacharjee and Jensen-Butler (2013) fo panel data models with SEM errors. Their algorithm requires of a consistent estimation of the covariances matrix of the errors obtained, for example, from LS residuals. Then this matrix is factorized to obtain the weighting matrix coherent both with the residual covariance matrix and the corresponding list of identification restrictions. Beenstock and Felsenstein (2012) present a similar approach for the case of pure panel data SLM model with unobserved random effects. We think that can be very illustrative to compare the results obtained with the three different approaches.

- The third issue that we are going to analyze in the paper expands a bit further our previous discussion. After estimating the weighting matrices corresponding to the Polish case in the last decades, we hope to be able to characterize formally the changing pattern of the network of interactions and formulate hypotheses about its functioning. This would allow us to parameterized the spatial weights, in terms of their basic fundamentals. Assuming that we had success in this point, the next natural step is to estimate the relations using the corresponding algorithm (QML, GMM depending on their nature) . These estimates can be used to produce forecasts about the foreseeable evolution of the Polish regional system in the medium and long run

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