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^{Q1} Neighbourhood GMM estimation of dynamic panel data models

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ABSTRACT

A new approach is developed for estimation of short dynamic panel data models with spatially correlated errors. The method employs an additional set of moment conditions that become available for each *i*—specifically, instruments with respect to the individual(s) which unit *i* is spatially correlated with. These moment conditions are non-redundant and remain informative even if the data generating process is close to a unit root one. The proposed GMM estimator is consistent and asymptotically normally distributed. An extensive Monte Carlo study also builds a GMM estimator that combines spatial and standard instruments. This estimator appears to perform very well under a wide range of parametrisations in terms of both bias and root mean square error. The proposed method is illustrated using crime data based on a panel of 153 local government areas in NSW, spanning a period of 5 years.

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1. Introduction

Dynamic panel data models are popular in microeconomic applications because the autoregressive parameter typically (23) measures persistence that is due to costs of adjustment or habit formation, and thereby it has structural significance (see e.g. Bond, 2002). Similarly, in macroeconomic applications the autoregressive parameter contains useful information about the long-run relationship between variables and characterises the dynamic adjustment of macroeconomic aggregates (see e.g. Breitung, 2015). In the empirically common situation where the number of time series observations is small, the Generalised Method of Moments (GMM) estimator, studied by Arellano and Bond (1991) and Arellano and Bover (1995) among many others, has proved particularly popular—not only for uncovering dynamic relationships in economic applications, but also as a base for further theoretical development (see e.g. De Wachter and Tzavalis, 2012). One reason for this may be that GMM provides consistent and asymptotically efficient inference under a relatively small set of assumptions, particularly with respect to the regressors. Furthermore, the method is computationally straightforward to implement and is part of most estimation packages in statistics and econometrics nowadays.

Despite its optimal asymptotic properties as well as its empirical popularity, there has been a growing concern regarding the finite sample behaviour of the estimator when the instruments used are weak. For instance, Blundell and Bond (1998) showed that the first-differenced GMM estimator, hereafter FD GMM, suffers from a weak instruments problem when either the autoregressive parameter approaches unity, or the variance of the individual effects grows large. Consequently, they put forward a 'system' GMM estimator, hereafter SYS GMM, which makes use of instruments with respect to equations in levels. These are valid provided that the process is mean-stationary. Bun and Windmeijer (2010) have shown that a similar problem actually arises with SYS GMM as well, since the instruments with respect to the equations in levels can also be

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weak, although the problem may manifest itself in a different way. The literature is far from conclusive on this matter. For 1 2 example, Hayakawa (2009) and Hayakawa and Nagata (2015) show that mean-stationarity is actually the worst case scenario for FD GMM, and departures from stationary initial conditions may mitigate the weak instruments problem even in cases 3 where the data are highly persistent. Similarly, Kruiniger (2009) establishes that the nature of weak instruments depends л on the distributional properties of the initial observations and derives local asymptotic approximations to the finite-sample 5 distributions of DIF GMM and SYS GMM. 6 In this paper we relax the commonly placed assumption that the errors are independent across individuals; see e.g. Anderson and Hsiao (1981, pg. 598), Arellano and Bond (1991, pg. 278), Blundell and Bond (1998, pg. 118). Instead, we 8 specify a spatial autoregressive structure in the errors. Spatial correlations may arise in economic applications due to spillq over effects on the basis of economic and social distance (Conley, 1999) or relative location (Anselin, 2001). One strand of the 10 spatial literature models dependence through spatial lags of the dependent variable (and/or the covariates), in which case the 11 spatial parameter has structural significance. Methods developed for such models have been proposed by Lee (2007), Lee and 12 Yu (2010), Kelejian and Prucha (2010), among others. Another strand of the spatial literature models dependence through 13 the errors, in which case such dependence is viewed as nuisance (e.g. Anselin, 1988; Baltagi et al., 2003; Mutl, 2006; Kapoor 14 et al., 2007, among others). In this case the emphasis lies in obtaining a consistent estimator of the error variance-covariance 15 16 **O4** matrix in order to produce asymptotically valid inferences. Elhorst (2010) and Lee and Yu (2013) provide excellent recent surveys on spatial models. Notice that treating spatial dependence as nuisance is, in this respect, similar to the common 17 factor approach for modelling cross-sectional dependence (see e.g. Sarafidis and Wansbeek, 2012). 18 The present paper is associated closer with the second strand of research. The main contribution is to show that spatial 19 dependence can actually be used in a constructive way (literally); that is, aside from the well-understood requirement to 20 correct the standard errors in order to be able to produce asymptotically valid inferences, it turns out that spatial dependence 21 gives rise to an additional set of moment conditions-in particular, instruments with respect to the individual(s) which 22 unit i is spatially correlated with. In many practical circumstances these 'spatial moment conditions' are shown to be non-23 redundant in the sense that the asymptotic variance of the GMM estimator based on the enlarged set of moment conditions 24 is smaller than that of the GMM estimator using the smaller set of moment conditions, i.e. those instruments with respect 25 to individual *i* only. 26 Spatial instruments have actually been frequently used on several occasions, especially in the field of empirical 27 microeconomics; for instance, in the context of studying the effect of public insurance for children on their utilisation of 28 medical care, Currie and Gruber (1996) make use of the average eligibility for 'Medicaid' for children living in a given state 29 as an instrument for the eligibility of an individual child living in the same state. Klasing (2013) assesses the role of culture 30 05 in determining the quality of institutions by constructing instruments based on weighted averages of cultural attitudes that 31 are present in neighbouring countries. Similarly, Bellou (2015) examines the implications of internet diffusion on marriage 32 rates, making use of the population density in neighbouring areas to construct instruments for market size in a particular 33 area. Notwithstanding, to the best of our knowledge there has been no proper theoretical justification for such practice, and 34 this is essentially the subject of the present paper. 35 We put forward a GMM estimator that does not rely on first-differencing and is not sensitive to the initial conditions of 36 the data generating process. Moreover, it is not subject to the notorious weak instruments problem in that the properties of 37 the estimator do not depend on the value of the autoregressive parameter being sufficiently smaller than unity. Apart from 38 an interesting result per se, this is also practically important because economic series are often highly persistent, while 39 mean-stationarity cannot be theoretically justified in many applications (see e.g. Bun and Sarafidis, 2015), and the state of 40 41 the initial condition may be unknown. In an extensive Monte Carlo study we also build an estimator that combines spatial with standard instruments. Finite 42 sample evidence shows that both estimators perform well under a variety of circumstances. This includes the case where 43 the spatial weighting matrix is misspecified. 11 The structure of the paper is as follows. The following section specifies the model, discusses the basic assumptions 45 employed and derives the consistency and asymptotic normality of the GMM estimator that makes use of spatial moment 46 conditions. Section 3 analyses the properties of the spatial instruments and Section 4 investigates the performance of the 47 estimator in finite samples using simulated data. Section 5 provides empirical evidence on Becker's (1968) theory of a 48 'rational criminal' using a panel data set of 153 local government areas in NSW observed over the period 2004-2008. A 49 final section concludes. 50 2. Model specification and spatial moment conditions 51 2.1. Model 52 We consider the following panel AR(1) model 53 $y_{it} = \alpha y_{it-1} + u_{it}, \quad 0 < |\alpha| < 1; \ i = 1, \dots, N, \ t = 1, \dots, T,$ (1)5/ $u_{it} = \eta_i + \varepsilon_{it}; \quad \varepsilon_{it} = \rho \sum_{i=1}^N w_{ij,N} \varepsilon_{jt} + v_{it}; \ 0 < |\rho| < 1.$ (2)55 Please cite this article in press as: Sarafidis, V., Neighbourhood GMM estimation of dynamic panel data models. Computational Statistics and Data Analysis

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