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Spillover dynamics for systemic risk measurement using spatial financial time series models

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ABSTRACT

We extend the well-known static spatial Durbin model by introducing a time-varying spatial dependence parameter. The updating steps for this model are functions of past data and have information theoretic optimality properties. The static parameters are conveniently estimated by maximum likelihood. We establish the theoretical properties of the model and show that the maximum likelihood estimators of the static parameters are consistent and asymptotically normal. Using spatial weights based on cross-border lending data and European sovereign CDS spread data over the period 2009–2014, we find evidence of contagion in terms of high, time-varying spatial spillovers in the perceived credit riskiness of European sovereigns during the sovereign debt crisis. We find a particular downturn in spatial dependence in the second half of 2012 after the outright monetary transactions policy measures taken by the European Central Bank. Earlier non-standard monetary operations by the ECB did not induce such changes. The findings are robust to a wide range of alternative model specifications.

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1. Introduction

We propose a new parsimonious model to measure the time-varying cross-sectional dependence in European sovereign credit spread changes in order to investigate the effectiveness of non-standard monetary operations by the ECB in reducing contagion concerns during the European sovereign debt crisis. The model builds on the well-known spatial Durbin model for panel data. The strength of contemporaneous spillover effects is summarized in a single time-varying parameter: the spatial dependence parameter. We argue that this parameter may be interpreted as a measure of sovereign systemic risk that relates to the connectedness of the system in a similar way as the unconditional correlations of Forbes and Rigobon (2002). The changes in the dependence parameter can thus be labeled as contagion in the technical sense of Forbes and Rigobon (2002).

Our paper contributes to two strands of literature. First, we contribute to the applied spatial econometrics literature. Spatial models have been widely used in applied geographic and regional science studies, and have recently also been applied in empirical finance; see Fernandez (2011) for a CAPM model augmented by spatial dependences, Wied (2013), Arnold et al. (2013), Kelly et al. (2013), and Asgharian et al. (2013) for analyses of spatial dependences in stock markets, Denbee et al. (2014) for a network approach to assess interbank liquidity, and Saldias (2013) for a spatial error model to identify sector risk determinants. Keiler and Eder (2015) and Tonzer (2015) both use spatial lag models, to model CDS spreads of financial institutions and banking sector risks, respectively.

The above models, however, treat the spatial dependence parameter as static. To the best of our knowledge, explicitly endowing the spatial dependence parameter in the spatial Durbin model with time series dynamics is a new development. Allowing for such dynamics may be important empirically; see for example our financial systemic stability application in Section 5. We model the dynamics using the score-driven framework proposed by Creal et al. (2011, 2013) and Harvey (2013). Given the nonlinear impact of the time-varying parameter in the model, the theoretical properties of this model and the asymptotic properties of the maximum likelihood estimator (MLE) for the remaining static parameters are challenging and have not been established so far. We show under what conditions the filtered spatial dependence

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parameters are well behaved, such that the model is invertible. Invertibility is a key property for establishing consistency and asymptotic normality of the MLE; see for example Wintenberger (2013). We derive new conditions for the asymptotic properties of the MLE compared to Blasques et al. (2014), allowing for exogenous regressors to be part of the specification. We also discuss the information theoretic optimality of the model and illustrate in a simulation study that the model is able to track a range of different patterns for the time-varying spatial dependence parameter.

Second, we contribute to the literature that studies the dynamics of financial systemic risk in the context of a network of sovereigns or financial firms. Since the beginning of the European sovereign debt crisis in 2009, the sharp increases and comovements of sovereign credit spreads have been the subject of a growing number of empirical studies in finance. For instance, by employing an asset pricing model, Ang and Longstaff (2013) investigate the differences between U.S. and European credit default swap (CDS) spreads as a reflection of systemic risk. Lucas et al. (2014) and Kalbaska and Gatkowski (2012) use multivariate time series models to model comovements in European sovereign CDS spreads. Ait-Sahalia et al. (2014) model sovereign credit default intensities using multivariate jump processes. De Santis (2012) and Arezki et al. (2011) study credit risk spillover effects that are induced by rating events, such as downgrades of Greek government bonds. Leschinski and Bertram (2013) find contagion effects in European sovereign bond spreads using the simultaneous equations approach of Pesaran and Pick (2007). Caporin et al. (2013), on the other hand, employ Bayesian quantile regressions, and conclude that comovements in European credit spreads during the debt crisis are only due to increased volatilities, but not contagion.

Our approach differs from the studies above since we introduce cross-sectional correlation not only through contemporaneous error correlations, but also through spillovers induced by shocks to the regressors, such as stock market crashes or interbank lending rates. Furthermore, we explicitly offer financial sector linkages as the source of sovereign credit risk comovements. This view is supported by the results of Korte and Steffen (2015), Kallestrup et al. (2016), Gorea and Radev (2014), and Beetsma et al. (2012), in which cross-border exposures between international financial sectors are relevant drivers of sovereign credit spreads. By exploiting these debt interconnections as economic distances between sovereigns in our spatial model, we obtain a scalar time-varying (spatial) dependence coefficient. We interpret this parameter in the systemic context as the overall tendency for shock spillovers. Such changes to spillovers are directly linked to contagion as defined in the technical sense of Forbes and Rigobon (2002). As such, the spatial dependence coefficient provides a measure of changes in systemic risk and the market's perception of contagion within the euro area.

We organize the remainder of this paper as follows. Section 2 introduces our spatial score model with time-varying parameters, formulates the information theoretic optimality properties of the steps, and establishes the consistency and asymptotic normality of the maximum likelihood estimator. In Section 3, we provide Monte Carlo evidence of the model's ability to track different dynamic patterns in spatial dependence over time. Section 4 describes the data for our study on European sovereign CDS spread dynamics. Section 5 provides the results for our main model, its extensions and some alternative specifications. Section 6 concludes.

2. Spatial models with dynamic spatial dependence

2.1. Static spatial model for panel data

The Spatial Durbin Model (SDM) for panel data is given by

$$y_t = \rho\, Wy_t + \beta_1 \mathbf{1}_n + A_t\beta_2 + W\, A_t\beta_3 + e_t,$$
$$e_t \sim p_e(e_t;\, \Sigma, \lambda), \qquad t = 1, \dots, T, \tag{1}$$

where $y_t = (y_{1t}, \dots, y_{nt})'$ denotes a vector of n cross-sectional observations at time t, ρ is the spatial dependence coefficient, W is an $n \times n$ matrix of exogenous spatial weights, β_1 is an unknown scalar intercept, $\mathbf{1}_n$ is an $n \times 1$-vector of ones, A_t is an $n \times k$ matrix of exogenous regressors, β_2 and β_3 are $k \times 1$ vectors of unknown coefficients, respectively,[1] and e_t is an $n \times 1$ disturbance vector with multivariate density $p_e(e_t, \Sigma; \lambda)$, mean zero, unknown $k \times k$ covariance (or scale) matrix Σ, and other parameters describing the shape of the distribution are collected in the parameter vector λ. For example, if p_e is a Student's t distribution, λ contains the degrees of freedom parameter.

Model (4) implies that each entry y_{it}, for $i = 1, \dots, n$, of the vector y_t depends on the other entries y_{jt}, for $j \neq i$. For a moderately large n, we cannot estimate such a system of contemporaneous dependences without imposing further restrictions. The idea of a spatial dependence model is to specify the spatial weight matrix W as a function of geographic or economic distances, and in this way exogenously define a neighborhood structure between the cross-sectional units. It is standard practice to use a row-normalized weight matrix W such that $\sum_{j=1}^{n} w_{ij} = 1$ for $i = 1, \dots, n$, where w_{ij} is the (i, j)th element of W. The impact of the (spatially weighted) contemporaneous dependent variables Wy_t on y_t is captured by a scalar spatial dependence parameter ρ. For shocks to die out over space, we require $\rho \in (1/\omega_{min}, 1)$ where ω_{min} is the smallest eigenvalue of W; see for example Lee (2004).

In addition to the spatial lag of the dependent variable, the Spatial Durbin Model (1) features spatial lags of the individual-specific regressors. This implies that each panel unit's dependent variable may react to shocks to the regressor(s) of its neighboring units. The model formulation not only nests the widely used Spatial Lag Model (SLM) for $\beta_2 = 0$, it is also the reduced form of a model with spatial dependence in the error term, the so-called Spatial Error Model (SEM). The SEM has the form

$$y_t = \gamma_1 \mathbf{1}_n + A_t\gamma_2 + u_t, \quad u_t = \delta W u_t + e_t \tag{2}$$

where γ_1 and δ are unknown scalars, γ_2 is an unknown coefficient vector and e_t is defined as above. The model can be rewritten as

$$y_t = \delta W y_t + \widetilde{\gamma}_1 \mathbf{1}_n + (I_n - \delta W) A_t \gamma_2 + e_t \tag{3}$$

with $\widetilde{\gamma}_1 = \gamma_1(I_n - \delta W)$, which is a SDM model with $\beta_2 = \gamma_2$ and parameter restriction $\beta_3 = -\delta\gamma_2$, see also LeSage and Pace (2008).

In the following, we write the SDM as

$$y_t = \rho W y_t + X_t \beta + e_t \tag{4}$$

with $X_t := (\mathbf{1}_n : A_t : WA_t)$ and $\beta := (\beta_1, \beta_2', \beta_3')'$. It can be shown that this basic form can capture nonlinear feedback effects across units by rewriting it as

$$y_t = Z X_t \beta + Z e_t, \tag{5}$$

where we assume that the inverse matrix $Z = (I_n - \rho W)^{-1}$ exists, with I_n denoting the $n \times n$ identity matrix. Using an infinite power series expansion as in LeSage and Pace (2008), we obtain

$$y_t = X_t\beta + \rho W X_t \beta + \rho^2 W^2 X_t \beta + \cdots + e_t$$
$$+ \rho W e_t + \rho^2 W^2 e_t + \cdots . \tag{6}$$

Eq. (6) reveals that e_{it} and $x_{it}'\beta$ for unit i spill over to other units $j \neq i$. The extent of spillover depends on the relative proximity of j to i via the weight matrix W and the spatial dependence parameter ρ. At the same time, there are possible feedback effects back to unit

[1] Here, we assume that A_t only contains individual-specific regressors. In our empirical application, we also consider regressors that are common to all units. In this case, to avoid multicollinearity due to the row-normalization of W, $W A_t$ only comprises the subset of individual-specific regressors.

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